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The Analysis of Mortality Data, by Logistic and Compartmental Models, In Multiple Countries. Is It An Approach To Estimate How The Covid-19 Pandemic Could Last?

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***Abstract* - Currently, mathematical modeling plays a pivotal role in comprehending and examining the intricacies of the COVID-19 pandemic. This brief report uses official information from WHO to utilize a logistic and compartmental model in the COVID pandemic, applied across twelve countries, to infer the mortality asymptote, total deviance, and the moment from which the final period of the pandemic begins epidemic duration in order to estimate the duration of this pandemic. Our results based on the analysis of mortality data reflecting that can be conventionally 95% inferred to that the completion of the epidemic could ended in Spain (November 2022), South Africa (2023 February), Egypt (April 2023), France and Italy (June 2023), China (September 2023), Russia (November 2023), India (December 2023), USA (February 2024), Japan (July 2024), Israel (August 2024) and Germany (January 2025).**

Keywords - COVID-19; end date of epidemic; logistic model; compartmental model

I. INTRODUCTION

Globally, on 12:20 p.m. CEST, August 30, 2023, the World Health Organization (WHO) reported a total of 770,085,713 confirmed cases of coronavirus disease 2019 (COVID-19), with 6,956,173 deaths. Additionally, as of August 27, 2023, a total of 13,499,983,736 vaccine doses have been administered [1]. Nowadays, mathematical modeling plays a crucial role in understanding and analyzing the dynamics of the COVID-19 pandemic, but there is several mathematical modeling in this context as are i) transmission dynamics, which focus on capturing the spread and transmission dynamics of the SARS-CoV-2 virus considering factors such as the reproduction number (R0), the rate of infection, and the effectiveness of various control measures like social distancing and vaccinations [2,3]; ii) population heterogeneity where often account for population heterogeneity, considering fac-tors like age, pre-existing health conditions, and geographical variations incorporating demographic data and incorporate different subpopulations to capture variations in susceptibility, infection rates, and disease severity [4,5]; iii) intervention strategies which evaluate the effectiveness of different intervention strategies assessing the impact of measures like lockdowns, mask-wearing, contact tracing, and vaccinations in controlling the spread of the virus [6,7]; iv) data integration where models rely on real-time data to calibrate and validate their predictions integrating epidemiological data, such as case counts, hospitalizations, and deaths, as well as behavioral data like and adherence to public health guidelines [8,9], v) scenario analysis where is explored different what-if scenarios and assess the potential outcomes under varying conditions simulating the impact of different levels of compliance with preventive measures, the emergence of new variants, or changes in testing and surveillance strategies [10,11]; and vi) policy planning and forecasting which provide insights into the potential trajectories of the pandemic, helping policymakers anticipate healthcare needs, allocate resources, and design effective mitigation strategies to minimize the impact of the virus [12,13]. However, it is important to note that the field of mathematical modeling in the context of the COVID-19 pandemic is dynamic and continuously evolving. Our group have developed mathematical models both to evaluate the process of spreading COVID-19 [14] and to estimate the duration of epidemic and its phases [15]. The aim of this brief report is to use solving logistic and compartmental mortality equations in COVID pandemic applied in twelve countries and infer mortality asymptote, to estimate epidemic duration and the pandemic too.

II. MATERIALS AND METHODS

We use official information of twelve countries (China, Egypt, France, Germany, In-dia, Israel, Italy, Japan, Russia, South Africa, Spain and USA), obtaining from the WHO Coronavirus (COVID-19) Dashboard, which are publicly available at https://covid19.who.int/data. We collected the cumulative number of COVID-19 infections, recoveries, and deaths from February 3rd to April 30th, 2023, and stored this data in Excel files. Based on the biomathematical experience acquired, in particular that made about COVID-19 since the beginning of 2020 in Italy, we have chosen to use the same deterministic models used successfully in Italy [14,15] to analyze the mortality trend in other countries, the only “certain” figure because it is final and not debatable.

III. RESULTS

We define the integral equations of two models; logistic and compartmental. The logistic model works well in each of the individual phases. The asymptote of the entire multiphase process is determined by the sum of the partial net asymptotes. Furthermore the compartmental model, as currently structured, performs even better by averaging the three phases into a single one.

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For the logistic model is the following:

$$M(t) = A / [1+ q\ EXP(-kt)]$$

where:

M= M%= cumulative number of deaths per hundred inhabitants up to time t.

A= M% max (asymptote).

q= numerical value linked to the formation of A.

k= constant of velocity at which A is formed.

t= number of months passed since the beginning of the epidemic

For the compartmental model, it can be developed as follows:

It is assumed that the end of the epidemic will occur when the Mortality index reach-es a numerical value very close (for example, ≥95%) to the asymptotic one and will keep it stable over time. The choice to analyze the trend of mortality to try to predict the duration of the epidemic was made on the bases of some evidence:

- The trend of mortality (observed data) develops in phases.
- The overall outcome of an epidemic depends on the number of deaths.

It is reasonable to draw in Figure 1.

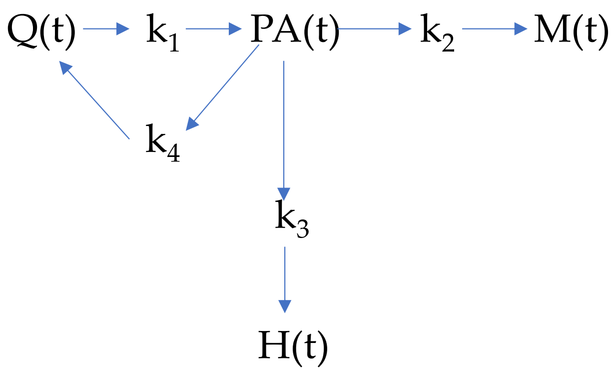

Fig. 1. Scheme of compartmental model

In which:

Q (t) is the [%] population susceptible to infection at time t

PA(t) is the value [%] of positive-alive/population at time t

where PA=infected-healed-deaths

M (t) is the Mortality % at time t

H (t) is the Healing % at time t

k_1 is the speed of entry into PA

$K = (k_2 + k_3 + k_4)$ is the exit speed from PA

k_2 is the entry speed into M

k_3 is the entry speed into H

k_4 is the re-entry speed into Q

The model is described by the following system of differential Equations:

$$\begin{cases} dQ/dt = -k_1Q + k_4PA \\ dPA/dt = -K\ PA + k_1Q \\ dM/dt = +k_2PA \\ dH/dt = +k_3PA \end{cases}$$

The formal solution of the system consists of the following integral Equations:

$$Q(t) = Q_0\cdot[(K-\alpha)/(\beta-\alpha)]*[EXP(-\alpha\cdot t)] - Q_0\cdot[(K-\beta)/(\beta-\alpha)]*[EXP(-\beta\cdot t)]/(\beta-\alpha)]$$
$$PA(t) = [k_1Q_0/(\beta-\alpha)]\cdot[EXP(-\alpha\cdot t) - EXP(-\beta\cdot t)]$$
$$M(t) = [k_2Q_0/(K-k_4)]-[k_1k_2Q_0/\alpha(\beta-\alpha)]\cdot[EXP(-\alpha\cdot t)]+[k_1k_2Q_0/\beta(\beta-\alpha)]\cdot[EXP(-\beta\cdot t)]$$
$$H(t) = [k_3Q_0/(K-k_4)]-[k_1k_3Q_0/\alpha(\beta-\alpha)]\cdot[EXP(-\alpha\cdot t)]+[k_1k_3Q_0/\beta(\beta-\alpha)]\cdot[EXP(-\beta\cdot t)]$$

Where:

t = number of months since the beginning of the epidemic.

$Q_0 = 1 = 100\%$ is the entire not infected population at the beginning.

α e β are the roots of the quadratic equation $s^2 + s\ (k_1+ K) + k_1K - k_1k_4$

where $k_1+K= \alpha+\beta$ and $k_1(K-k_4) = \alpha\beta$

Thus, the Mortality Equation, obtained from the resolution of the compartmental model (Figure 1) was used to obtain the best fit of the observed mortality data:

$$M(t) = [k_2Q_0/(K-k_4)]-[k_1k_2Q_0/\alpha(\beta-\alpha)]\cdot[EXP(-\alpha\cdot t)]+[k_1k_2Q_0/\beta(\beta-\alpha)]\cdot[EXP(-\beta\cdot t)]$$

The observed mortality curve and those calculated from both models, we showed in Figures 2-13 for twelve countries, including China, Egypt, France, Germany, India, Israel, Italy, Japan, Russia, South Africa, Spain and USA.

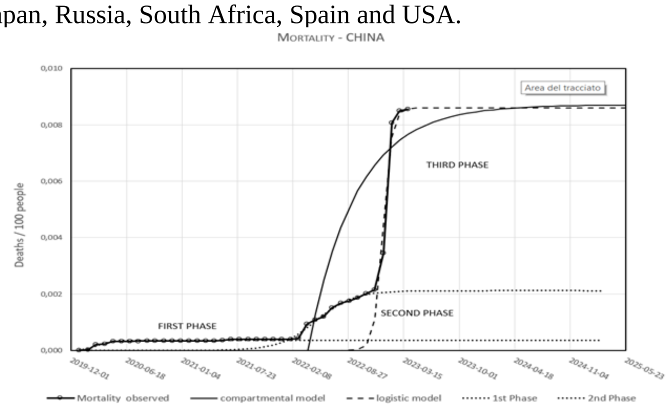

Fig. 2. Mortality trend in CHINA

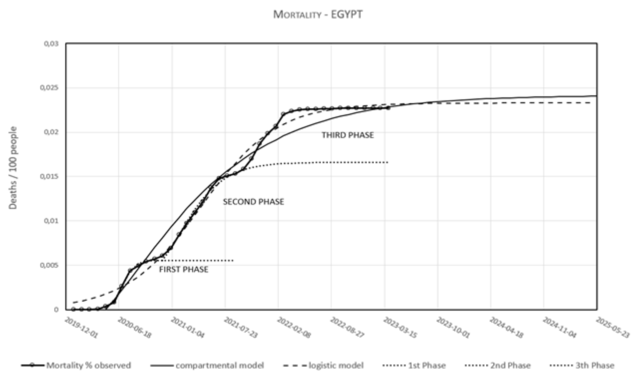

Fig. 3. Mortality trend in EGYPT

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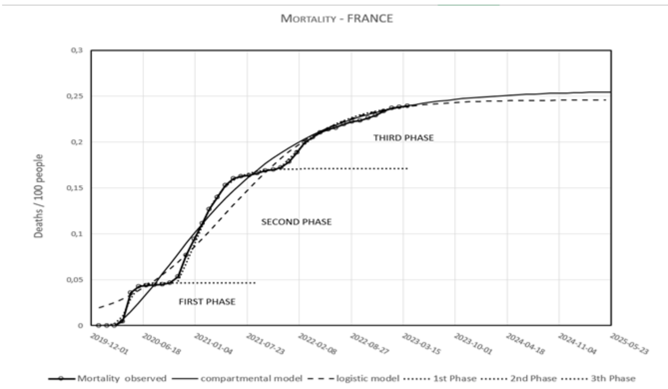

Fig. 4. Mortality trend in FRANCE

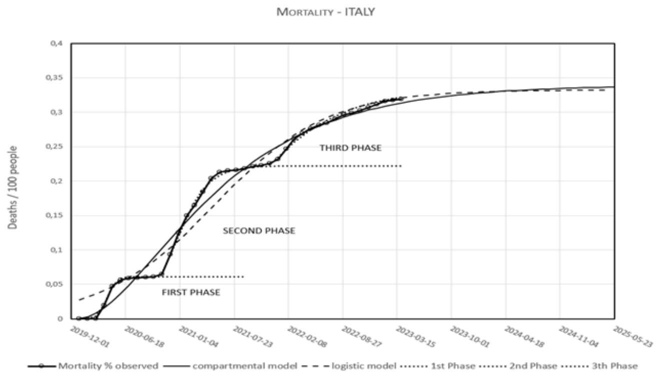

Fig. 8. Mortality trend in ITALY

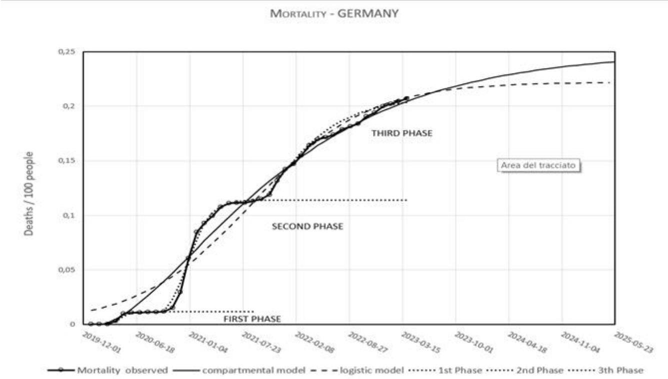

Fig. 5. Mortality trend in GERMANY

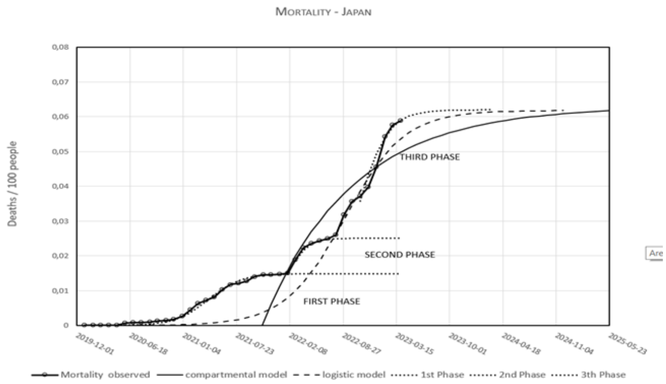

Fig. 9. Mortality trend in JAPAN

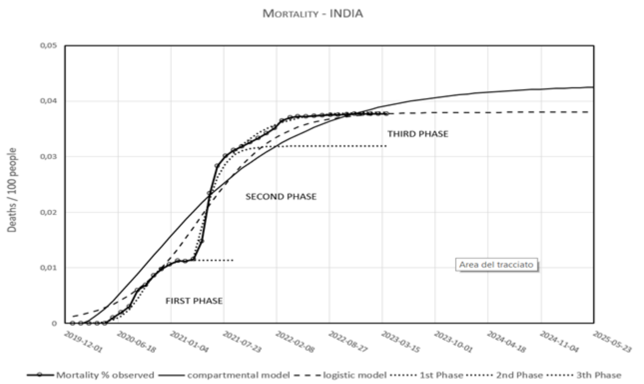

Fig. 6. Mortality trend in INDIA

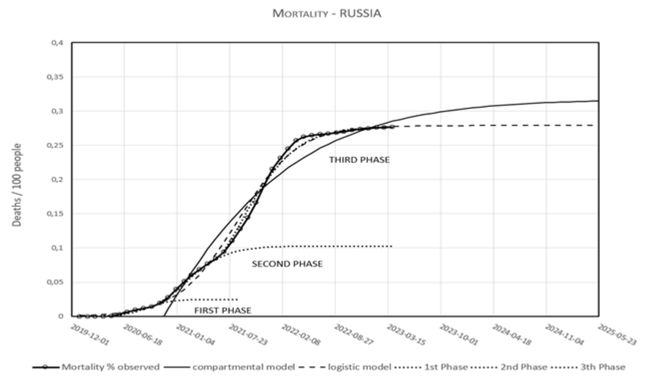

Fig. 10. Mortality trend in RUSSIA

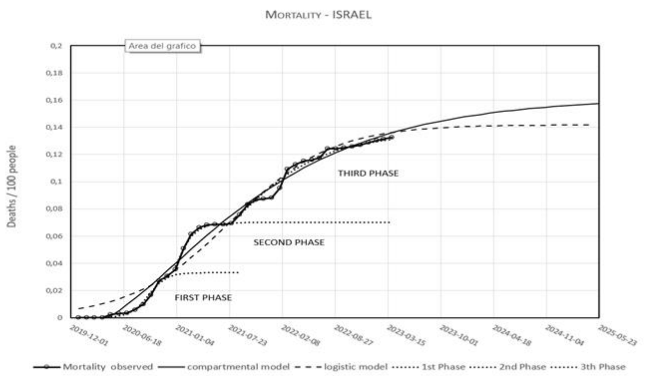

Fig. 7. Mortality trend in ISRAEL

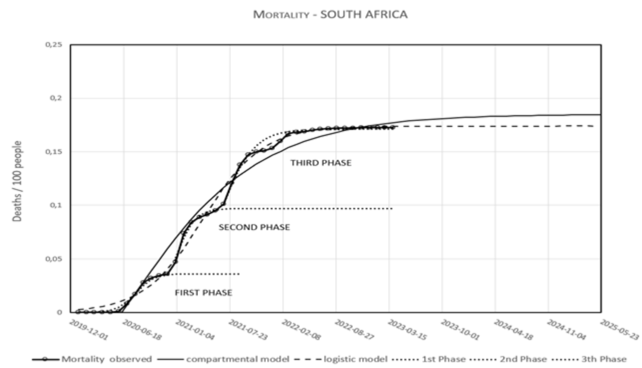

Fig. 11. Mortality trend in SOUTH AFRICA

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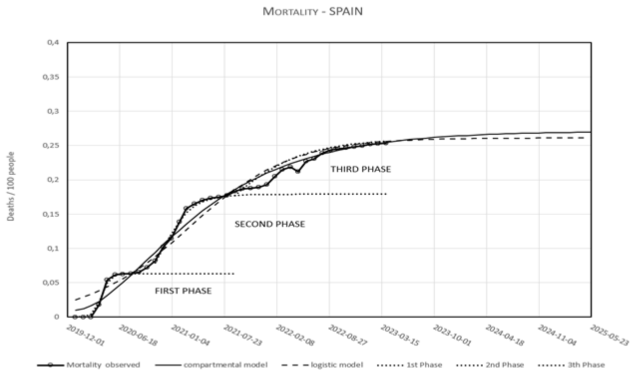

Fig. 12. Mortality trend in SPAIN

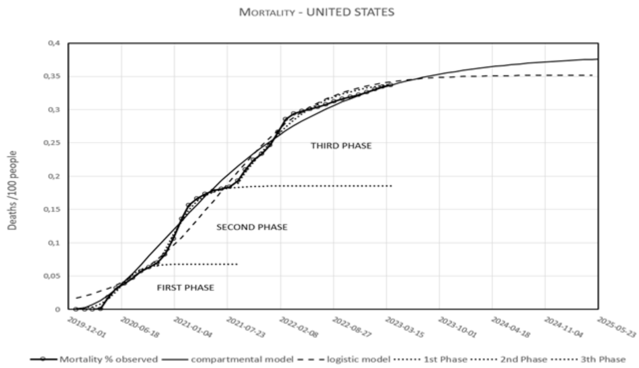

Fig. 13. Mortality trend in USA

Furthermore, Table 1 summarizes results from logistic and compartmental models from these twelve countries reflecting two mortality asymptote (95% and 99,5%), which estimate the time to reach mortality of 95% and 99.5% of the asymptote. total deviance

Based on the analysis of mortality data, it can be conventionally 95% inferred that the epidemic started the final period in Spain (November 2022), in Egypt (April 2023), in France and Italy (June 2023), but it will begin in China (September 2023), in Russia (November 2023), in India (December 2023), in United States (February 2024), in Japan (July 2024), in Israel (August 2024), in Germany (January 2025).

IV. DISCUSSION

It is important to remember that there are two conditions for the epidemic to end. First, the mortality rate must reach its peak and remain stable over time. Second, the number of active positive cases must decrease towards zero. Based on the data collected from January 1, 2020, to March 31, 2023, the observed mortality follows a three-phase pat-tern that is not always evident. It is clear in Egypt, France, Germany, Israel, Italy, South Africa, Spain, the United States, where the three phases are mainly regulated by decreasing speeds. In India and Japan, mortality seems to form in two steps at increasing speed. The first step combines the first two phases and the second coincides with the third phase. The mortality curves in Russia and China show a drastically different trend from the rest of the countries studied. In Russia, the trend in mortality seems monophasic (Figure 10). Probably as if adequate prevention and treatment systems had not been used during the development of the epidemic. In China, the third phase exhibits a more rapid and intense increase in mortality (Figure 2). Since being infected is a prerequisite for mortality, the start of the mortality curve is always delayed until the beginning of the epidemic. As shown in Figure 1, this onset differs not only due to geographical distances but also because of the quantity and speed of connections between various regions scattered across the world. Particularly, the mortality pattern observed in China appears to contradict the gradualness rule that typically characterizes biological processes. Hence, it is reasonable to assume that the artifact is not due to the inadequacy of the compartmental model but rather human error. The decision to implement both lockdown and quarantine measures for an extended period is apparent. Consequently, it appears as if the mortality curve began two years later.

Table 1. Estimated Time to reach both 95% and 99.5% of the maximum mortality.

COUNTRY	MODEL	DEVIANCE on the set of mortality data [10^{-3}]	CUMULATIVE DEATHS updating by April 30, 2023		ESTIMATED TIME REQUIRED TO REACH Mortality Asymptote	
			Observed	Calculated	= 95% date	>= 99.5% date
CHINA	Logistical	1.418	120,958	121,398	2023, May	2025, January
	Compartmental	1,157.371	120,958	110,592	2023, September	2026, December
EGYPT	Logistical	0.024	24,826	25,321	2022, April	2025, October
	Compartmental	0.070	24,826	25,099	2023, April	2027, May
FRANCE	Logistical	7.350	162,868	162,466	2022, December	2028, June
	Compartmental	3.770	162,868	163,177	2023, June	2029, May
GERMANY	Logistical	8.166	173,044	174,425	2023, May	2029, May
	Compartmental	4.908	173,044	172,236	2025, January	2032, September
INDIA	Logistical	0.235	531,533	531,907	2022, June	2026, January
	Compartmental	0.519	531,533	555,821	2023, December	2031, June
ISRAEL	Logistical	2.285	12,492	12,835	2023, February	2027, July
	Compartmental	1.051	12,492	12,894	2024, August	2029, March
ITALY	Logistical	13.827	189,738	190,841	2023, January	2029, January
	Compartmental	7.093	189,738	189,360	2023, June	2029, November
JAPAN	Logistical	1.427	74,528	69,622	2023, August	2026, May
	Compartmental	699.516	74,528	64,015	2024, July	2029, December
RUSSIA	Logistical	2.298	398,305	398,361	2022, July	2025, October
	Compartmental	142.807	398,305	412,680	2023, November	2030, September
SOUTH AFRICA	Logistical	1.237	102,595	103,209	2022, February	2025, March
	Compartmental	7.001	102,595	105,723	2023, February	2027, October
SPAIN	Logistical	8.623	120,715	121,678	2022, September	2028, March
	Compartmental	4.421	120,715	121,488	2022, November	2028, December
UNITED STATES	Logistical	7.75	1,124,063	1,096,752	2022, December	2028, March
	Compartmental	4.881	1,124,063	1,134,509	2024, February	2032, October

The first significant mortality figures were detected in China in December 2019, followed by France, Italy, Spain, Germany, Egypt, and the United States in March 2020. South Africa, Israel, and Russia observed significant mortality in April 2020, and India and Japan experienced it in May 2020. From the deviance values, it is evident that both models interpret the observed mortality data as if the entire process did not result from the sum of phases but rather as a single continuous phase (Table 1), except for Russia, Japan, and China (Figure 2). Particularly, the mortality pattern observed in China appears to contradict the gradualness rule that typically characterizes biological processes. Hence, it is reasonable to assume that the artifact is not due to the inadequacy of the compartmental model but rather human error. The decision to implement both lockdown and quarantine measures for an extended period is apparent.

Regarding the prediction of the epidemic/pandemic duration, it should be noted that the models used differ from their original design. The logistic model describes the distribution and growth in the number of deaths, while the compartmental model describes the distribution and growth of deaths as the final outcome driven by the positive-alive cases. Estimating the duration can be done using both models, both within each phase and for the overall trend. To ensure reliable estimates, it is necessary to collect observed mortality data from the onset time to the inflection time. The experimental curve is graphically constructed based on the observed data. At the inflection point, the first derivative reaches its maximum value, and the second derivative is zero, indicating a change in sign. Estimates of the epidemic duration in each country vary depending on the model used (Table 1). The compartmental model provides higher estimates compared to the logistic model. This corresponds to the presence of positive-alive cases considered only in the compartmental model. Therefore, the persistence of positive-alive cases leads to the prolongation of the epidemic. This additional period of time could be defined as the final phase of the epidemic. Since this study was conducted on a representative sample comprising 45% of the global population, it is reasonable to consider mortality modeling analysis as a valuable approach for estimating the duration of the epidemic/pandemic.

According to Lu et al. [16] stated that predictions in real-life situations enhance ecological validity compared to estimates made in artificial laboratory settings. Smart and Combrink [17] indicated that an epidemic reaches its end when the burden of disease falls below a clearly defined and normative ‘epidemic threshold’, as is obtained in our results. In fact, our study is focused in the medical end of this epidemic due to that Charters [18] suggested three endings to an epidemic as are the end of disease (the medical end), the end of the crisis and regulations (the political end), and the return to normalcy (the social end). According to this author, the end periods should serve to look both forward and backward, with the aim of applying the so-called "lessons learned" that can prevent future outbreaks. The importance of epidemiology professionals is crucial in addressing this situation, as there are still policymakers in some countries [19] who are not aware of the distinction between the two possible medical end states of an epidemic, namely ‘herd immunity’ (understood as a mechanistic model) and the so-called ‘suppressed equilibrium’ (achieved by suppressing contacts among individuals). Liu et al. [20] pointed out another important element for the conclusion of the epidemic, such as economic investment, as the higher the budget for incentives, the faster the epidemic will end. Therefore, financial incentives can have the advantage of reducing the total cost required to prevent the spread of the disease.

Consequently, the conclusion can be drawn that the pandemic may can start the final period with the first country reaching 95% of the maximum mortality (Spain, November 2022) and end it with the last country exceeding 99.5% (United States, October 2032), assuming that the boundary conditions (such as a complex and integrated system of prevention and treatment) remain stable and that a new viral variant does not emerge, resulting in a new epidemiological phenomenon.

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