Cardiovascular disease (CVD): assessment, prediction and policy implications

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Abstract

Background: The study aims to predict and assess cardiovascular disease (CVD) patterns in highly affected countries such as Pakistan, India, China, Kenya, the USA, and Sweden. The data for CVD deaths was gathered from 2005 to 2019.

Methods: We utilized non-homogenous discrete grey model (NDGM) to predict growth of cardiovascular deaths in selected countries. We take this process a step further by utilizing novel Synthetic Relative Growth Rate (RGR) and Synthetic Doubling Time (Dt) model to assess how many years it takes to reduce the cardiovascular deaths double in numbers.

Results: The results reveal that the USA and China may lead in terms of raising its number of deaths caused by CVDs till 2027. However, doubling time model suggests that USA may require 2.3 years in reducing the cardiovascular deaths.

Conclusions: This study is significant for the policymakers and health practitioners to ensure the execution of CVD prevention measures to overcome the growing burden of CVD deaths.

Keywords: Cardiovascular disease, CVD, Relative growth rate, Doubling time model, assessment, forecast

Introduction

The upsurge of the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) infection in early 2020 caused a disease pandemic known as COVID-19 [1, 2]. There is practically no country in the world which is not influenced by COVID-19 and the health services worldwide have never operated under this tremendous burden. Everything begun in Wuhan [3], China, but it has expanded exponentially all over the world. The core of the pandemic then moved to Europe and the US [4]. Studies also shown that patients with Cardiovascular Disease (CVD) are especially at great risk of COVID-19 mortality owing to their frailty and vulnerability [5, 6]. Patients with pre-existent CV risk factors and CVDs are among the most vulnerable with significantly greater risk of developing SARS-CoV-2 infection, acquiring CV complications associated with COVID-19, and having undesirable consequences [7].

Since the number of deaths has been increasing globally due to different reasons, CVD is one of the world’s most significant causes of mortality and morbidity. During the past decade, the number of deaths from CVD has increased by 12.5% globally [8, 9]. There are various reasons behind this progressive number of cardiovascular deaths. In 2016, the primarily cause of total global burden of CVD was ischemic heart disease (IHD) contributed to 49% of total burden of CVD, followed by stroke with 33% of total CVD burden. In comparison, other CVD causes account for a significantly lower percentage of the global disease burden [10].

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CVDs have affected all the income level countries, especially low- and middle-income countries (LMIC) contribute the greatest portion to the overall CVD burden, specifically in terms of deaths at younger ages than in high-income countries, because of scarce human and financial resources [11–13]. Whereas, several of the largest LMIC had an increase in the overall burden of CVD; in decreasing pattern of percent burden increase, those included: India (15.4%), Bangladesh (27.4%), Indonesia (8.8%), China (6.6%), the Philippine (25.3%), and Mexico (19.7%) [14]. However, the CVD burden remains the most significant per capita in Eastern Europe and Central Asia. While, East Asia and South Asia are roots to the increased CVD burden, because of their growing and aging of the populations [15]. The 2016 Global Burden of Diseased Disease (GBD) report reveals that non-communicable diseases (NCDs) comprise 40% of the total age standardized global disease burden for women and about 50% of the global standardized men’s overall age burden. CVD alone accounted for 20% of women’s total burden and 24% of men’s total burden [16]. The frequency of steady or growing CVD Disability Adjusted Life-Year (DALY) epidemiological drivers vary across different countries. In countries such as Japan, a reduced CVD mortality rate has been offset by accelerated population aging. A slight rise of the CVD rate is associated with population ageing and limited resources in South Asian countries such as Pakistan, India, and Bangladesh [17].

Several epidemiological studies have forecast future trends in the occurrence of CVD and mortality rates for all age groups in various countries of the world [18–20], yet little is known about the absolute burden of deaths. To prepare for future cardiovascular care needs with certainty, the purpose of this study is to forecast the number of deaths caused by CVD from 2020 to 2027 of six highly affected countries which include Pakistan, India, China, Kenya, the USA and Sweden. We employed advanced mathematical modeling, namely Non-Homogenous Discrete Grey Model (NDGM) to predict the cardiovascular deaths of selected countries. The grey forecasting models, especially, the NDGM model, can be superior to other forecasting models in the context of small samples and poor information [21]. Hence, we have utilized NDGM model in the current paper to predict the future trends of CVD of top six countries globally. Further, a novel Synthetic Relative Growth Rate (RGR) and Synthetic Doubling Time (D_t) models employed to undertake a comparative analysis of CVD relative growth rate among six countries. Moreover, Mean Absolute Percentage Error (MAPE) % criterion was used to measure the accuracy of NDGM model. Hence, present research is a pioneer study to forecast relative growth and required time to reduce the number of deaths double in number caused by CVD among six countries. The study is principally significant for the policymakers to convey, empower and stimulate the execution of CVD prevention approaches to end this growing burden of CVD during the ongoing COVID-19 pandemic and time ahead.

The rest of paper follow as: Section 2 represent the research methodology. Whereas the result and discussion section are presented in section 3. Finally, conclusion, policy implications along with study limitations presented in last section is study.

**Research methodology**

This section provides steps involved in development of NDGM model. Additionally, synthetic RGR and synthetic D_t models have been discussed to analyze the growth and time of CVD deaths for selected countries. Finally, the performance evaluation of NDGM model through MAPE is also elaborated in this section.

**Data source and study population**

The CVD number of deaths data was abstracted from the official website of Our World in Data for the period 2005–2019. The top six countries which are Pakistan, India, China, Kenya, USA and Sweden with highly affected from cardiovascular deaths were selected, globally. The source of the data available at Our World in Data was the global burden of disease (GBD) collaborative network (2016), World Health Organization (WHO) and Institute for health metrics and evaluation (IHME) 2017. Grey system software (v8.0) has been used to forecast cardiovascular deaths for the period of 2020 to 2027 by NDGM. However, MATLAB and MS EXCEL were also used to solve NDGM. The current analysis and modeling methodology were employed for the first time in the study of forecasting CVD related deaths. The structure of forecasting the CVD deaths is operationalized in this study presented in Fig.1.

**Grey forecasting model**

In 1982 Deng Julong originally introduced the concept of a Grey Systems Theory (GST) as a scientific theory for predicting uncertain system, which involves limited and inadequate information. Ultimately, theoretical forecasts based on the grey framework surpassed the standards of statistical and mathematical methods [22]. Theory of grey systems has been applied successfully in several fields so far [23–25] and grey prediction theory is a significant branch of the theory of grey systems. There are five major types of grey prediction, such as time series forecasts, calamity forecasts, seasonal calamity forecasts, topological
forecasts, and systemic forecasts. Till date, GS theory has introduced a variety of theories and techniques like grey mathematics, grey modeling, grey forecasting, grey clustering, grey decision making, grey programming, grey relational analysis, and grey control, which has been effectively implemented in various fields and has shown satisfactory results [26, 27]. The key benefit of grey theory is that it can manage both with limited and uncertain information with great precision. It functions as an analytical tool particularly in situations where data is inadequate.

Nonhomogeneous discrete grey model (NDGM)
In order to predict data, there are different types of grey models, we will analyze NDGM to predict future cardiovascular deaths. The NDGM system is designed on the basis of law of approximation non-homogenous exponential growth in accordance with assumptions of a sequence of real data [24] [28]; Xie et al. [25] recommended that the actual data sequence is a concurrenee with a homogenous pattern like GM (1, 1). The accuracy level of NDGM model is considerably improved over other grey models so far as mean sequence
value and value set of intervals [29]. NDGM model has been utilized in various fields, for example, in a study the electricity consumption of Turkey was predicted and analyzed the NDGM as best fit and more accurate prediction model over other grey forecasting models [30]. Whereas, Duan et al. forecast the crude oil consumption in China and investigated that NDGM showed superior performance [31].

\( \hat{x}^{(0)} \), represent the original data sequence and \( \hat{x}^{(1)} \) follows the accumulated data sequence in NDGM model so, we can write as follows:

\[
\begin{align*}
\hat{x}^{(1)}(L+1) &= \beta_1 \hat{x}^{(1)}(L) + \beta_2 L + \beta_3 \\
\hat{x}^{(1)}(1) &= \hat{x}^{(1)}(1) + \beta_4
\end{align*}
\]

Where, \( \hat{x}^{(1)}(L) \) is the forecasting value of \( x^{(1)} \) along with parameters \( \beta_1 \), \( \beta_2 \), \( \beta_3 \) and \( \beta_4 \). So, we can write the above equation in matrix form as: this: if \( L = 1, 2, \) and 3 ... n-1

\[
\begin{bmatrix}
\hat{x}^{(1)}(2) \\
\hat{x}^{(2)}(3) \\
\vdots \\
\hat{x}^{(1)}(n)
\end{bmatrix} =
\begin{bmatrix}
\beta_1 \\
\beta_2 \\
\beta_3
\end{bmatrix}
\begin{bmatrix}
\hat{x}^{(1)}(1) & 1 \\
\hat{x}^{(2)}(2) & 2 \\
\vdots & \vdots \\
\hat{x}^{(1)}(n-1) & L-1 \\
\hat{x}^{(1)}(n) & 1
\end{bmatrix}
\]

The input data shows constant sequence in single case in order to satisfy NDGM parameters \( \beta_1, \beta_2, \beta_3, \) and \( \beta_4 \) by applying the following relation:

\[
\hat{\beta} = (\hat{B}^T\hat{B})^{-1}\hat{B}^T\hat{Y} = [\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4]^T
\]

The following formula to be used to calculate \( \beta_4 \) for minimizing the sum of square error:

\[
\hat{\beta}_4 = \frac{\sum_{t=1}^{n-1} \sum_{l=1}^{L-1} \hat{x}^{(1)}(L+1) - \beta_1 \hat{x}^{(1)}(1) - \beta_2 \sum_{l=1}^{L-1} \beta_1 L - 1 - \beta_3}{1 - \sum_{t=1}^{n-1} (\beta_4^{(L)})^t}
\]

For further knowledge about NDGM model, its parameter and properties, Liu et al. (2010) is referred [25].

Performance evaluation approach of NDGM

We employed mean absolute percentage error (MAPE) to evaluate the accuracy of NDGM model. The formula to calculate MAPE % is as follows:

\[
\text{MAPE(\%)} = \frac{1}{n} \sum_{k=1}^{n} \left| \frac{y^{(0)}(k) - \hat{y}^{(0)}(k)}{y^{(0)}(k)} \right| \times 100
\]

Where \( y^{(0)}(k) \) represents the original sequence of data and \( \hat{y}^{(0)}(k) \) denotes the forecasting sequence data values.

Relative growth rate (RGR) and doubling time (D\(_{t}\)) analysis

To best of our knowledge, there is no model available to check the growth rate for cardiovascular deaths. In this manner, RGR model was used to analyze the relative growth rate of cardiovascular deaths for selected countries [32]. Two parameters (\( D_t \) and RGR) were employed in order to forecast the number of deaths caused by CVD of selected countries by utilizing NDGM model. The equation of RGR is given by,

\[
\text{RGR} = \ln \left( \frac{L_2}{L_1} \right)
\]

Where \( L_2 \) denotes the cumulative number of cardiovascular deaths in year \( t_2 \) & \( L_1 \) represent the cumulative number of cardiovascular deaths in year \( t_1 \), as in our case, the equation can be reduced to

\[
\text{RGR} = \ln \left( \frac{L_2}{L_1} \right)
\]

The \( D_t \) is the time required for publications to reduce the number of cardiovascular deaths for a given RGR is represented as:

\[
D_t = (t_2 - t_1) \ln \left( \frac{L_2}{L_1} \right)
\]

In our case, it can be written as:

\[
D_t = \ln \left( \frac{L_2}{L_1} \right)
\]

Synthetic RGR and synthetic doubling time model

In any case, if the RGR and \( D_t \) make an alternate pattern, when compared with that of actual data pattern create issue, in this regard synthetic Relative Growth Rate (RGR\(_{syn}\)) and Synthetic Doubling Time (D\(_{syn}\)) models have been introduced [33]. The equation for Synthetic Relative Growth Rate (RGR\(_{syn}\)) model can be written as follows:

\[
\text{RGR}_{syn} = \theta (\text{RGR}_{original}) + (1-\theta) (\text{RGR}_{forecast})
\]

Whereas \( \text{RGR}_{original} \) denotes the Relative Growth Rate of original data and \( \text{RGR}_{forecast} \) explains the Relative Growth Rate of predicted values. However, \( \theta \) indicate relative weights coefficient and its value can be taken as 0.5 in general.

The Synthetic Doubling Time (D\(_{syn}\)) model is presented as:

\[
D_{syn} = \theta (D_{original}) + (1-\theta) (D_{forecast})
\]

Here, \( D_{original} \) demonstrates the Doubling Time obtained from original data values, whereas \( D_{forecast} \)
indicate Relative Growth Rate based on forecasting data values.

**Results**

We employed NDGM to forecast the relative growth of cardiovascular deaths among six participated countries. The calculated simulated values for the data 2005–2019 are shown in Tables 1, 2, 3, 4, 5, and 6. Table 1 shows the forecasts results for Pakistan. The values obtained from MAPE % demonstrate the effectiveness level of 97.05% which shows NDGM as a best-fit grey model to forecast number of deaths caused by CVD. The simulated values based on NDGM showed an increasing trend for future. Figure 1 has been shown to better understand the comparison between actual data and the simulated NDGM data from 2005 to 2027 against the increasing deaths pattern for CVD in Pakistan.

With the turn of the century, CVDs became the leading cause of mortality in India. Table-2 represents the results from India with the MAPE accuracy level of 98.35%. The NDGM based simulated values also showed an inclined pattern in progressive number of cardiovascular deaths in future.

Table 3 represents the results for China. The forecast values based on NDGM simulated data showed an anticipated trend until 2027. The MAPE accuracy level turned out to be 96.88%. The NDGM model findings are found consistent with a range of other cardiovascular disease predictions in China, as the burden of CVD was increasing and primary and secondary prevention is likely to be core health policy priorities in the immediate future [34, 35].

Likewise, Tables 4, 5 and 6 represents the results for Kenya, USA and Sweden with MAPE accuracy level of 97.77, 96.8 and 97.74% respectively (Table 8). These findings are similar with some prior findings in which increasing trends have been reported [36]. According to a study in USA if projected trends in ischemic stroke mortality continue, increase in US stroke deaths will outpace overall population growth, with a doubling in deaths by the year 2032 [37]. For an easy and clear comparison of cardiovascular raising trends, Fig. 2a-f can be seen. All participated countries showed an increasing

| Table 1 Forecasting cardiovascular deaths in Pakistan |
|-----------------------------------------------------|
| Years | Original Data | NDGM | Cumulative | RGR | RGR Mean | Dt | Mean Dt |
|-------|---------------|------|------------|-----|-----------|----|---------|
| 2005  | 295,320       | 295,320 | 295,320 | 0.699 | 0.223 | 1.051 | 2.397 |
| 2006  | 298,835       | 297,535 | 594,156 | 0.411 | 1.582 | 1.913 |
| 2007  | 302,305       | 302,502 | 896,461 | 0.295 | 1.913 | 2.158 |
| 2008  | 307,782       | 307,896 | 1,204,244 | 0.295 | 1.913 | 2.349 |
| 2009  | 313,037       | 313,753 | 1,517,82 | 0.231 | 2.158 |
| 2010  | 319,323       | 320,113 | 1,836,606 | 0.191 | 2.349 |
| 2011  | 326,241       | 327,019 | 2,162,848 | 0.164 | 2.504 |
| 2012  | 334,172       | 334,517 | 2,497,021 | 0.144 | 2.9 |
| 2013  | 342,768       | 342,660 | 2,839,790 | 0.129 | 2.644 |
| 2014  | 352,846       | 351,502 | 3,192,636 | 0.117 | 2.883 |
| 2015  | 362,180       | 361,102 | 3,554,816 | 0.107 | 2.924 |
| 2016  | 372,096       | 371,527 | 3,926,909 | 0.100 | 3.12 |
| 2017  | 381,421       | 382,847 | 4,308,331 | 0.093 | 3.072 |
| 2018  | 395,139       | 399,214 | 3,95,139 | 0.201 | 1.914 |
| 2019  | 408,486       | 412,578 | 803,625 | 0.230 | 0.351 |
| 2020  | 422,979       | 422,605 | 1,226,605 | 0.265 | 1.887 | 2.125 |
| 2021  | 438,716       | 1,665,321 | 0.7521 | 1.087 |
| 2022  | 455,804       | 2,121,126 | 0.212 | 2.112 |
| 2023  | 474,360       | 2,595,486 | 0.252 | 2.423 |
| 2024  | 494,508       | 3,089,995 | 0.2174 | 2.521 |
| 2025  | 516,386       | 3,606,381 | 0.300 | 2.656 |
| 2026  | 540,143       | 4,146,525 | 0.268 | 2.721 |
| 2027  | 565,939       | 4,712,464 | 0.228 | 2.905 |
| MAPE % | 1.56 |

**Abbreviations:** EGM even grey model, DGM discrete grey model, NDGM nonhomogeneous discrete grey model, RGR relative growth rate, Dt doubling time
trend in raising their number of cardiovascular deaths, except for Sweden. A study has reported decline in mortality and incidence of cardiovascular related diseases since 1980s in Sweden. Changes in lifestyle have helped to break the increasing trend in CVD [38]. The outcomes reveal that the MAPE accuracy level for NDGM in case of India is found slightly higher than the rest of the five countries whereas Pakistan, Kenya and Sweden showed almost same MAPE accuracy level. The average MAPE accuracy level for NDGM showed a value of 97.44% (Table 8). The anticipated future trends in cardiovascular deaths for the participated countries compel to focus on the importance of increased investment in prevention and treatment of CVD.

**Table 2** Forecasting cardiovascular deaths in India

| Years | Original Data | NDGM | Cumulative | RGR | RGR Mean | Dt | Mean Dt |
|-------|---------------|------|------------|-----|----------|----|---------|
| 2005  | 1,653,599     | 1,653,599 | 1,653,599 | 0.431 | 0.224    | 1.026 | 2.362   |
| 2006  | 1,734,072     | 1,722,462 | 3,387,671 | 0.312 | 0.217    | 1.199 |        |
| 2007  | 1,818,917     | 1,822,164 | 5,206,588 | 0.257 | 0.169    | 1.268 |        |
| 2008  | 1,909,307     | 1,918,236 | 7,115,895 | 0.217 | 0.169    | 1.268 |        |
| 2009  | 1,996,194     | 2,010,811 | 9,112,089 | 0.169 | 0.169    | 1.268 |        |
| 2010  | 2,095,862     | 2,100,015 | 11,207,951| 0.157 | 0.169    | 1.268 |        |
| 2011  | 2,197,149     | 2,185,971 | 13,405,100| 0.157 | 0.169    | 1.268 |        |
| 2012  | 2,285,131     | 2,268,798 | 15,690,230| 0.14  | 0.169    | 1.268 |        |
| 2013  | 2,351,070     | 2,348,609 | 18,041,301| 0.126 | 0.169    | 1.268 |        |
| 2014  | 2,418,358     | 2,425,515 | 20,459,659| 0.115 | 0.169    | 1.268 |        |
| 2015  | 2,490,513     | 2,499,621 | 22,950,172| 0.107 | 0.169    | 1.268 |        |
| 2016  | 2,583,709     | 2,571,028 | 25,533,881| 0.098 | 0.169    | 1.268 |        |
| 2017  | 2,632,780     | 2,639,836 | 28,166,660| 0.271 | 0.169    | 1.268 |        |
| 2018  | 2,706,138     | 2,712,540 | 2,706,138 | 0.19  | 0.169    | 1.268 |        |
| 2019  | 2,770,027     | 2,790,214 | 5,476,166 | 0.617 | 0.169    | 1.268 |        |
| 2020  | 2,831,590     | 8,307,755 |           |      |          |      |        |
| 2021  | 2,890,911     | 11,198,666| 0.431     | 0.266 | 1.825    | 2.143 |        |
| 2022  | 2,948,073     | 14,146,739| 0.234     | 2.217 |         |      |        |
| 2023  | 3,003,153     | 17,149,892| 0.293     | 2.342 |         |      |        |
| 2024  | 3,056,228     | 20,206,120| 0.264     | 2.522 |         |      |        |
| 2025  | 3,107,371     | 23,313,490| 0.243     | 2.608 |         |      |        |
| 2026  | 3,156,651     | 26,470,142| 0.327     | 2.777 |         |      |        |
| 2027  | 3,204,138     | 29,674,280| 0.190     | 2.862 |         |      |        |

MAPE % 2.88%

**Abbreviations:** EGM even grey model, DGM discrete grey model, NDGM nonhomogeneous discrete grey model, RGR relative growth rate, Dt doubling time

The relative growth rates and doubling time model have been employed to calculate the relative growth of cardiovascular deaths and an expected time to reduce the deaths in selected countries. Table 7 represents the ranking order of six countries for an estimated RGR and doubling time (Dt) as per original and simulated data. The RGR equation of original data showed a ranking order given below:

China (0.236) > USA (0.229) > India (0.224) > Pakistan (0.223) > Kenya (0.212) > Sweden (0.208)

To calculate the required time for cardiovascular death reduction among six countries based on original data, the following sequence was observed as per doubling time (Dt) model:

China (2.330) < India (2.362) < Pakistan (2.397) < Kenya (2.400) < Sweden (2.464) < USA (2.514)

The above-mentioned findings demonstrate that the relative growth of cardiovascular deaths in China as an upper middle-income country and USA as a high-income country rank higher followed by India, Pakistan,
Kenya and Sweden based on original data. On the contrary, the doubling time model suggest that developed countries like USA and Sweden require an additional time and endeavors to reduce cardiovascular deaths double in number than in developing countries (India, Pakistan, China, Kenya). Therefore, the relative growth rate can be a source of competitive edge among developing and developed countries.

Likewise, we utilized NDGM-based simulated data to find out the status of deaths due to CVD for the period from 2020 to 2027. As indicated by RGR sequence, the following results was acquired:

\[
\text{USA}^{(0.329)} > \text{China}^{(0.275)} > \text{Pakistan}^{(0.269)} > \text{India}^{(0.266)} > \text{Kenya}^{(0.261)} > \text{Sweden}^{(0.254)}
\]

Approximately same sequence was observed based on the simulated data. For the period 2020–2027, USA and China may endure progressively number of deaths due to CVD in terms of RGR i.e. (3.29%) and (2.75%) respectively followed by Pakistan, Kenya, India and Sweden.

As per doubling time (D_t) model, the following pattern of results is obtained:

\[
\text{China}^{(2.117)} < \text{Pakistan}^{(2.125)} < \text{India}^{(2.143)} < \text{Kenya}^{(2.190)} < \text{USA}^{(2.193)} < \text{Sweden}^{(2.893)}
\]

Our findings also revealed that USA and Sweden need relatively additional timespan to double reduce the number of cardiovascular deaths, followed by Kenya, India, Pakistan and China.

By using NDGM (based on actual and simulated data), we forecast the number of cardiovascular deaths for the period from 2020 to 2027.

### Synthetic RGR and synthetic DTM for cardiovascular deaths

Presently a query arises here eventually as which country may endure maximum number of deaths by CVD in the long run. Therefore, to respond the query synthetic

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**Table 3** Forecasting cardiovascular deaths in China

| Years | Original Data | NDGM | Cumulative | RGR | Mean RGR | D_t | Mean D_t |
|-------|---------------|------|------------|-----|----------|-----|---------|
| 2005  | 3,123,852     | 3,123,852 | 3,123,852 | 0.616 | 0.236 | 1.070 | 2.330   |
| 2006  | 3,080,393     | 3,030,930 | 6,204,245 | 0.408 | 0.940 | 1.590 |         |
| 2007  | 3,126,022     | 3,171,122 | 9,330,267 | 0.352 | 1.681 | 2.104 |         |
| 2008  | 3,260,751     | 3,308,158 | 12,591,018 | 0.242 | 2.257 | 2.257 |         |
| 2009  | 3,440,057     | 3,442,107 | 16,031,075 | 0.263 | 2.257 | 2.257 |         |
| 2010  | 3,610,887     | 3,573,039 | 19,641,062 | 0.263 | 2.257 | 2.257 |         |
| 2011  | 3,744,796     | 3,701,023 | 23,386,759 | 0.165 | 2.459 | 2.459 |         |
| 2012  | 3,844,071     | 3,826,124 | 27,230,830 | 0.161 | 2.576 | 2.576 |         |
| 2013  | 3,872,996     | 3,948,408 | 31,103,826 | 0.153 | 2.651 | 2.651 |         |
| 2014  | 4,039,145     | 4,067,937 | 35,142,971 | 0.141 | 2.726 | 2.726 |         |
| 2015  | 4,221,832     | 4,184,775 | 39,364,803 | 0.133 | 2.862 | 2.862 |         |
| 2016  | 4,344,334     | 4,298,982 | 43,709,137 | 0.105 | 2.924 | 2.924 |         |
| 2017  | 4,377,972     | 4,410,616 | 48,087,109 | 0.095 | 3.062 | 3.062 |         |
| 2018  | 4,519,736     | 4,532,154 | 45,197,366 | 0.099 | 3.111 | 3.111 |         |
| 2019  | 4,626,399     | 4,678,514 | 9,146,135 | 0.168 | 0.524 | 0.524 |         |
| 2020  | 4,730,659     | 4,730,659 | 13,876,794 | 0.254 | 0.275 | 1.240 | 2.117   |
| 2021  | 4,832,572     | 18,709,366 | 0.524 | 0.275 | 1.240 | 2.117   |
| 2022  | 4,932,189     | 23,641,555 | 0.334 | 2.146 | 2.146   |
| 2023  | 5,029,563     | 28,671,118 | 0.193 | 2.315 | 2.315   |
| 2024  | 5,124,744     | 33,795,862 | 0.284 | 2.451 | 2.451   |
| 2025  | 5,217,781     | 39,013,642 | 0.174 | 2.514 | 2.514   |
| 2026  | 5,308,722     | 44,322,365 | 0.258 | 2.612 | 2.612   |
| 2027  | 5,397,616     | 49,719,981 | 0.215 | 2.701 | 2.701   |

**MAPE %** 4.15%

**Abbreviations:** EGM even grey model, DGM discrete grey model, NDGM nonhomogeneous discrete grey model, RGR relative growth rate, D_t doubling time
indices by original and forecasting values have been calculated.

By using synthetic indices, the sequence obtained for RGR is as follows:

$$\text{USA}_{0.271} > \text{China}_{0.255} > \text{India}_{0.251} > \text{Pakistan}_{0.248} > \text{Kenya}_{0.246} > \text{Sweden}_{0.231}$$

As per synthetic doubling time model $D_t$, we obtained a sequence as follows:

$$\text{China}_{2.179} < \text{India}_{2.263} < \text{Pakistan}_{2.270} < \text{Kenya}_{2.276} < \text{Sweden}_{2.297} < \text{USA}_{2.386}$$

Both sequences are found almost similar to the sequences obtained against the actual data thus the results are aligned with the actual data and the feasibility of the synthetic models has also been tested successfully.

**Discussion**

In spite of significant reductions in incidence and mortality, CVDs are still the greatest reason for death globally, both in terms of health and economic cost. We built up a forecasting framework to estimate the expected number of cardiovascular deaths in Pakistan, India, China, Kenya, the USA and Sweden by utilizing the most accurate methodology of the grey forecasting framework. Results depicted that grey prediction model was effectively applied to forecast the number of deaths caused by CVD for the period from 2020 to 2027. In addition, this study also suggests an expected time to reduce the number of deaths double in numbers using doubling time ($D_t$) formula. All six countries showed an increasing trend in forecasting number of deaths due to CVD for the period 2020–2027, except for Sweden. However, the results indicated that USA and China are more likely to suffer from cardiovascular deaths in future followed by Pakistan, Kenya, India and Sweden. Though China found prone to suffer maximum deaths in future, the doubling time ($D_t$) suggests less time expected to control and prevent from cardiovascular deaths double in number.
The results confirm that developed countries need relatively more time to reduce the deaths double in numbers whereas, developing countries require less time to do so. Whereas the USA and China may lead in terms of raising its cardiovascular mortality in future. While in case of lower middle-income countries, India and Pakistan are more likely to suffer from cardiovascular deaths in future followed by Kenya and Sweden. Figuratively speaking, a sword of Damocles hangs over the people of the USA and China, indeed most of the entire world, for the near future. Through CVD prevention and the implementation of workable approaches, we are foreseeing a future wherein the CVD epidemic is being tamed.

Statistics from various parts of the world show a large percentage of cerebrovascular and CV associated diseases in patients with COVID-19, which posed several questions about the higher sensitivity of patients with any of these comorbidities to the novel coronavirus, and also the function of CVD in progression and COVID-19 patient prognosis. Patients with Cardiovascular diseases should be monitored by their healthcare professionals with special preventive procedures for COVID-19 infection. The level of severity of both the primary respiratory syndrome and risk of adverse events is elevated in patients associated with COVID-19 and also with pre-existing cardiovascular diseases. Hospitals and healthcare networks must embrace a comprehensive approach to provide all patients with the best quality treatment, irrespective of their COVID-19 status. This is especially significant for the cardiology community, considering patients with prior symptoms of CVD and risk factors are potentially more likely to experience COVID-19 and encounter undesirable consequences. As the rate of infection rises, several cardiac patients may seek immediate treatment for either COVID-19 associated diseases or common cardiac complications. Most of these patients would need a cardiac intervention while at the same time getting SARS-CoV-2 infection.

COVID-19, triggered by SARS-CoV-2, is a worldwide pandemic emerging in real time. Cardiovascular and associated comorbidities are very common in COVID-19 patients and those are at greater risk of morbidity and mortality. COVID-19 raised an additional constraint on

| Years | Original Data | NDGM | Cumulative | RGR | RGR Mean | Dt | Mean Dt |
|-------|---------------|------|------------|-----|----------|----|---------|
| 2005  | 857,472       | 857,472 | 857,472 |     |          |    |         |
| 2006  | 842,430       | 817,100 | 1,699,903 | 0.684 | 0.228   | 1.072 | 2.514  |
| 2007  | 827,191       | 817,591 | 2,527,094 | 0.528 | 1.618   |    |         |
| 2008  | 823,970       | 818,325 | 3,351,065 | 0.442 | 1.958   |    |         |
| 2009  | 814,684       | 819,425 | 4,165,749 | 0.219 | 2.216   |    |         |
| 2010  | 805,696       | 821,073 | 4,971,446 | 0.166 | 2.426   |    |         |
| 2011  | 817,311       | 823,541 | 5,788,758 | 0.152 | 2.546   |    |         |
| 2012  | 821,111       | 827,238 | 6,609,869 | 0.135 | 2.713   |    |         |
| 2013  | 830,227       | 832,776 | 7,440,096 | 0.128 | 2.828   |    |         |
| 2014  | 840,356       | 841,071 | 8,280,452 | 0.107 | 2.928   |    |         |
| 2015  | 857,259       | 853,496 | 9,137,711 | 0.089 | 3.145   |    |         |
| 2016  | 880,573       | 872,107 | 10,018,285 | 0.052 | 3.309   |    |         |
| 2017  | 902,270       | 899,984 | 10,920,556 | 0.036 | 3.414   |    |         |
| 2018  | 941,740       | 942,407 | 941,740   | 0.341 | 2.045   |    |         |
| 2019  | 1,004,285     | 1,014,248 | 1,946,025 | 0.215 | 2.000   |    |         |
| 2020  | 1,097,970     | 1,097,970 | 3,043,995 |     |          |    |         |
| 2021  | 1,238,298     | 4,282,293 | 4,282,293 | 0.124 | 0.329   | 3.412 | 2.193  |
| 2022  | 1,448,492     | 5,730,785 | 5,730,785 | 0.291 | 2.104   |    |         |
| 2023  | 1,763,336     | 7,494,121 | 7,494,121 | 0.468 | 2.302   |    |         |
| 2024  | 2,234,934     | 9,729,054 | 9,729,054 | 0.361 | 2.431   |    |         |
| 2025  | 2,441,328     | 12,170,382 | 12,170,382 | 0.224 | 2.554   |    |         |
| 2026  | 2,999,418     | 15,169,801 | 15,169,801 | 0.320 | 2.856   |    |         |
| 2027  | 3,050,121     | 18,219,922 | 18,219,922 | 0.383 | 2.935   |    |         |

MAPE % 1.02%
pre-existing CVDs. Findings from COVID-19 infection with a significant number of patients showed that fatality rate was of 10.5% for CVD among 72,314 COVID-19 cases [39]. Studies have revealed that there is a greater risk of mortality among patients hospitalized with COVID-19 due to CVD. Given the growing number of COVID-19 patients other than regular clinical presentations of illness, CVD in COVID-19 infected patients appear to be alarming [40, 41]. CVDs have played an important role in patient outcomes infected from the virus. Thus, careful review and monitoring of CVD in COVID-19 patients are required, from diagnosis to bedside.

CV associated complications have been identified in prior respiratory infections with related etiology and their occurrence affects the severity of the illness, so even pneumonia related hospitalization is found related with long-term and short-term risk of CVD [42]. Infection from viruses lead to an imbalance in cardiac supply and demand, as well as an increase in systemic inflammation. Consequently, patients with pre-existing CVD are more likely to experience acute cardiac complications, and thrombosis, and lead to severe infections. An investigation from a meta-analysis analyzed pooled prevalence of CVD in COVID-19 infected patients in various countries. The following are the findings of the meta-analysis: the US (24%), Brazil (50%), Netherlands (44%), Germany (46%), Iran (4%), Italy (25%), China (8%), South Korea (11%), Spain (17%), Switzerland (71%), United Kingdom (15%), and France (48%) Fig. 3a. The prevalence of CV complications in infected patients was shown to be substantially correlated with ICU admissions and mortality in that meta-analysis Fig. 3b [44].

However, valid information to assess the exact burden of CVD is inadequate in many parts of the world, which compels the foundation of nationwide prevention and management policies. It is clear that while many advances have been introduced in our comprehension of worldwide CVD epidemiology, there is wide variation present in data, mainly in MICs and LICs such as Pakistan and India. In these regions, there is a requirement for significantly advanced frameworks for the supervision of risk factors and disease and for strategies

### Table 6 Forecasting cardiovascular deaths in Sweden

| Years | Original Data | NDGM | Cumulative | RGR | RGR Mean | D_t | Mean D_t |
|-------|---------------|------|------------|-----|----------|-----|----------|
| 2005  | 38,572        | 38,572 | 38,572     |     |          |     |          |
| 2006  | 38,317        | 38,716 | 76,889     | 0.690 | 0.208   | 1.064 | 2.464   |
| 2007  | 38,053        | 37,881 | 114,943    | 0.402 | 0.102   | 1.064 | 2.464   |
| 2008  | 37,525        | 37,151 | 152,469    | 0.283 | 0.075   | 1.064 | 2.464   |
| 2009  | 36,792        | 36,513 | 189,262    | 0.216 | 0.055   | 1.064 | 2.464   |
| 2010  | 35,644        | 35,955 | 224,007    | 0.173 | 0.042   | 1.064 | 2.464   |
| 2011  | 35,642        | 35,467 | 260,550    | 0.147 | 0.032   | 1.064 | 2.464   |
| 2012  | 35,070        | 35,041 | 295,620    | 0.126 | 0.024   | 1.064 | 2.464   |
| 2013  | 34,559        | 34,668 | 330,180    | 0.111 | 0.018   | 1.064 | 2.464   |
| 2014  | 33,961        | 34,342 | 364,141    | 0.098 | 0.013   | 1.064 | 2.464   |
| 2015  | 33,768        | 34,057 | 397,909    | 0.089 | 0.009   | 1.064 | 2.464   |
| 2016  | 33,710        | 33,808 | 431,619    | 0.081 | 0.007   | 1.064 | 2.464   |
| 2017  | 34,163        | 33,590 | 465,783    | 0.076 | 0.006   | 1.064 | 2.464   |
| 2018  | 33,399        | 33,410 | 33,399     | 0.028 | 0.003   | 1.064 | 2.464   |
| 2019  | 33,233        | 33,521 | 66,633     | 0.102 | 0.007   | 1.064 | 2.464   |
| 2020  | 33,087        | 99,721 |           |     |          |     |          |
| 2021  | 32,960        | 132,681|           | 0.321 | 0.254   | 2.100 | 2.893   |
| 2022  | 32,849        | 165,530|           | 0.221 | 0.184   | 2.765 |        |
| 2023  | 32,751        | 198,282|           | 0.381 | 0.305   | 2.864 |        |
| 2024  | 32,666        | 230,949|           | 0.253 | 0.203   | 2.943 |        |
| 2025  | 32,592        | 263,542|           | 0.212 | 0.162   | 3.764 |        |
| 2026  | 32,527        | 296,069|           | 0.116 | 0.090   | 3.888 |        |
| 2027  | 32,470        | 328,540|           | 0.304 | 0.244   | 3.978 |        |

**MAPE %** 2.02%

*Abbreviations: EGM even grey model, DGM discrete grey model, NDGM nonhomogeneous discrete grey model, RGR relative growth rate, D_t doubling time*
that can diminish CVD’s morbidity and mortality at a low cost in ways that are practical and sustainable. The former can be achieved with large but simple health surveys that gather reliable data on health behaviors, CVD associated risk factors, incidence, and mortality, and access to health care in every region of the world.

Though these predictions are sober, they do not need to become true, as CVD is potentially preventable. Improving risk factors at population level in the past obviously had a decisive effect on the reduction in death rates for CVD worldwide. Several studies have shown that there is a considerable decrease in CVD mortality rates among individuals with favorable levels of significant CVD risks [45] [8, 46]. Likewise, people who practice a healthy lifestyle face a comparatively lower risk of suffering from cardiovascular related diseases. A greater emphasis on prevention may therefore alter these anticipated trends in the future and eventually may overcome the growing pandemic of COVID-19.

**Limitations**

The present study has several limitations. The data from Our World in Data, however comprehensive and easily accessible to almost all countries and regions, is based on regularly available data from those countries and regions. Variations may occur in the robustness of the data selection and processing and reliability of the cause of the death. Secondly, these predictions are made for developed and developing countries data together, and their generalizability to other countries should be considered with caution. It should be acknowledged that there are many differences between developed and developing countries when comparing health-care systems and how diseases are dealt. We believe that this has kept our analysis conservative. Another limitation of the study is the application of single grey prediction model which is NDGM. The further research can be carried out by employing other grey prediction models and should consider the other regions of the world for more insight information.

**Table 7**

| Relative Growth rate/ Double Time | Ranking |
|----------------------------------|---------|
| RGR (original data)              | China(0.326) > USA(0.228) > India(0.224) > Pakistan(0.223) > Kenya(0.213) > Sweden(0.208) |
| D_t (Original Data)              | China(0.330) < India(0.330) < Pakistan(0.297) < Kenya(0.240) < Sweden(0.234) < USA(0.234) |
| RGR (Forecast Data)              | USA(0.328) > China(0.275) > Pakistan(0.269) > India(0.260) > Kenya(0.261) > Sweden(0.254) |
| D_t (Forecast data)              | China(0.211) < Pakistan(0.125) < India(0.143) < Kenya(0.140) < USA(0.193) < Sweden(0.263) |

**Fig. 2** a Simulative and Predictive values of NDGM for Pakistan. b Simulative and Predictive values of NDGM for India. c Simulative and Predictive values of NDGM for China. d Simulative and Predictive values of NDGM for Kenya. e Simulative and Predictive values of NDGM for USA. f Simulative and Predictive values of NDGM for Sweden.
Conclusion
In conclusion, CVD plays a key role in disease burden and mortality in COVID-19 patients. Since CVD complications in COVID-19 patients could be fatal, they must be carefully monitored and managed in the case of an acute illness. It is yet not clear whether the prevalence of cardiovascular comorbidities poses independent risk or if this is affected by other factors such as age etc. The results from the forecasting model against all selected countries showed an increasing trend in terms of raising its number of deaths due to CVD till 2027, except for Sweden. However, the growth rate for the USA (RGR: 2.71%) and China (RGR: 2.55%) was found relatively higher than the rest of the three countries. The findings also revealed that USA (2.3 years) and Sweden (2.2 years) may require relatively additional timespan to double reduce the number of cardiovascular deaths when compared with China (2.1 years). The findings of this study can aid policymakers, doctors, and front-line

Table 8 MAPE %

| Countries  | MAPE % (NDGM) |
|------------|---------------|
| Pakistan   | 2.95          |
| India      | 1.65          |
| China      | 3.12          |
| Kenya      | 2.23          |
| USA        | 3.20          |
| Sweden     | 2.26          |
| Average MAPE % | 2.56    |
| Overall accuracy Level | 97.43 |
healthcare workers in making evidence-based decisions and reducing the mortality and morbidity associated with this 21st-century pandemic.

Abbreviations

- CVD: Cardiovascular disease
- NDGM: Non-homogeneous discrete grey model
- EGM: Even Grey Model
- DGM: Discrete Grey Model
- SARS-CoV-2: Severe acute respiratory syndrome coronavirus 2
- RGR: Relative Growth Rate
- DC: Doubling Time
- GST: Grey Systems Theory
- IHD: Ischemic Heart Disease
- LMICs: Low- and middle-income Countries
- GBD: Global Burden of Disease
- NCDs: Non-communicable diseases
- DALY: Disability adjusted life-years

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Authors’ contributions

SR wrote the first draft of the article and conceptualized the overall study. SR and MI are involved in the data analysis. SR, ER and MI wrote the final manuscript. ZJL is responsible for project administration and supervision of the manuscript. All authors contributed to a second and third iteration of the manuscript, and everyone read and approved the final manuscript.

Availability of data and materials

The data used in the current study is available publicly at www.ourworldindata.com.

Declarations

Ethics approval and consent to participate

This study used secondary data and did not involve human subjects directly, informed consent was not obtained from the patients.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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