COVID-19 vaccine distribution: exploring strategic alternatives for the greater good

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Abstract
The dire state of the COVID-19 pandemic crisis symbolized the urgency for efficient distribution and administration of vaccines to combat the virus as the most urgent public health service. This paper presents a prototype multi-criteria decision support model based on goal programming that can effectively support vaccination plans for the greater good of society. The optimization goals of the model include minimizing the number of fatalities and risk of spreading the disease, while complying with government health agency's priority guidelines for vaccination. This study applied the model to a real-world dataset to demonstrate how it can be effectively applied as a decision support tool for vaccine distribution plans and manage future pandemics.

Keywords COVID-19 · Vaccine distribution priorities · Multiple-objective decision modeling · Goal programming · Decision support systems

1 Introduction

In December 2020, the United States Food and Drug Administration (FDA) approved the emergency use authorization of the two leading COVID-19 vaccines produced by Pfizer/BioNTech (Lovelace Jr. 2020) and Moderna (Miller and Edwards 2020). A third vaccine produced by Johnson & Johnson was approved for distribution in February 2021 (Fda.gov 2021). These authorizations consist of a historic turning point in the fight against the pandemic that has taken more than one million lives in the US and about 6.3 million worldwide as of May 2022 (Johns

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Hopkins University 2022). While vaccine administration is now well underway in many countries, the pandemic is far from under control. In addition, new variants of the virus require the development and distribution of additional booster shots. Many developing countries around the world are still waiting for the supply of vaccines from developed nations. Thus, it is important to design an effective decision model for rapid vaccine distribution based on management science, "the ubiquitous science of better" (Nikolopoulos et al. 2021), to lower the number of deaths, manage hospital capacity, and return to a near normal state soon.

In the US, the center for disease control and prevention (CDC) and other agencies established vaccine distribution priorities. In the first phase, healthcare workers and residents at long-term care facilities had the top priority to receive the vaccine (Gillespie 2020). Once the first phase of vaccination is completed, the next step would be to prioritize and deliver to the general population. Such delivery is not on a "first-come, first-served" basis. Instead, healthcare practitioners and state officials must provide the vaccines among the various priority groups to satisfy multiple objectives, such as minimizing the time required to vaccinate the entire eligible population, minimizing mortality, and underutilizing hospital capacities (CDCMMWR 2020). This study was motivated by the overwhelming danger of the global pandemic. COVID-19 has completely disrupted the daily lives of almost everyone in the world. This is the reason why the effective management of vaccine distribution is such an urgent public service issue, the very motivation for this study.

The authors communicated with representatives from several sectors that are involved in vaccine distribution planning: two professors at noted medical schools (a clinician/academic physician and a public health faculty), two newspaper editors/reporters who have developed objective macro views on COVID-19 based on their frequent contacts with government and public health decision-makers, and government policy makers at the Ministry of Health and Public Policy in a European country. The discussion with the above experts and opinion leaders provided first-hand knowledge about the challenges of the COVID-19 vaccination program. Specifically, these experts provided the assurance that there is a need for a decision support model that can apply administration priorities based on important factors that are relevant at a given time (virus spread phase) or place (country, city, county, etc.). In addition, the decision support tool should be able to help attain multiple goals: reduce the mortality rate, minimize the number of new infections, and achieve herd immunity as soon as possible. Finally, the decision-making model should be able to address not only current vaccine distribution-related issues, but also be able to help with possible future challenges such as expected booster shots and new variant vaccines, and even preparing for inevitable future pandemics.

The current CDC guidelines imply that age, medical conditions, and occupation (e.g., frontline or essential workers) (AMO) are important health factors in the fight against the COVID-19 pandemic, in addition to other measures such as wearing masks, physical distancing, and avoiding crowds. While older people are more vulnerable to the disease and have a higher risk of death, so are people with prior medical conditions. Concurrently, certain segments of the population, such as school children and essential workers, have a significant role in controlling the spread of COVID-19. CDC believes that the current vaccination priorities among

these population segments would be effective in lowering death rates, minimizing the risk of spreading the virus, minimizing overutilization of healthcare facilities, and achieving herd immunity soon. This paper offers answers to what population subgroups must be vaccinated to: (1) comply with CDC and state guidelines, (2) avoid the risk of spreading the disease, and (3) minimize the number of individuals that will succumb to the disease. In this paper, a prototype goal programming (GP) model is developed which combines the above three criteria to allow the decision-maker to effectively assign different priorities to population subgroups that need to be vaccinated.

The rest of the paper is organized as follows. In the next section a review of relevant literature is provided, including COVID-19 as the most destructive pandemic in the global age and vaccine distribution strategies, as well as properties and previous application studies of GP in the healthcare industry. Then, a prototype GP model is developed using the age, medical condition, and economic function as population classification criteria. In Sect. 3, the proposed GP model using a real-world COVID-19 dataset from kaggle.com is presented. Finally, in the discussion section, the significance of the study and its implications are elaborated; then recommendations based on the findings to public health policy makers, healthcare practitioners, and state officials are provided; and the paper concludes with limitations of the study and future research directions.

2 Literature review

2.1 The COVID-19 pandemic

The onslaught of COVID-19 is not just one destructive wave, but repeated flare-ups as witnessed in many countries (Daly and Rolander 2021). The waves of virus resurgence and new variants are threatening the hope of speedy recovery from the destructive force of the pandemic. Recently, several countries reintroduced economic lockdowns due to the resurgence of COVID-19 cases resulting from new variants (Leatherby 2021). Thus, governments, scientists, businesses, and communities around the world are trying to find the best approaches to contain the virus in order to return to normality as soon as possible (Devezas 2020).

The two important approaches to managing the pandemic involve the following: (1) preventing the spread of the virus and controlling virus resurgence through sound government directives and tracking (Lee and Trimi 2021; Sainz-Pardo and Valero 2021), while concurrently developing effective vaccines and rapidly administering them to the population for reaching herd immunity; and (2) managing infection cases by finding right treatment methods and cures. For the first approach, implementing sound practices recommended by credible agencies such as CDC, as well as a set of directives issued by the federal government and further reinforced by state/local governments, is imperative. Advanced technologies such as artificial intelligence (AI), internet of things (IoT), big data analytics, virtual/augmented reality (VR/AR), blockchain, 3-D printing, smart sensors and robots, and mobile location systems have been innovatively applied to learning about the virus (for treatment

and vaccination) and containing its spread (tracking and civic behavior) (Brem et al. 2021; Martin and Yoon 2020; Nigma et al. 2021).

2.2 COVID-19 vaccine distribution strategies

The obvious best solution to managing the pandemic is to vaccinate a sufficient proportion of the population, in addition to those who were infected and recovered, to develop herd immunity. Although there exists no exact percentage of the population that need to be vaccinated to achieve herd immunity, as the exact number of people who already had the virus is not known, the scientific community estimates that 58–94 percent of 18 + age group would need to be vaccinated (Apple et al. 2020). Undoubtedly, delivering billions of vaccine doses globally is one of the greatest logistical challenges ever undertaken, in addition to the economic aspects of the vaccine development. During the early stages of the vaccination program, demand for vaccine is expected to exceed supply. Thus, countries need to develop priority lists of vaccine recipients, which are based on common factors of age, medical conditions, and jobs (healthcare providers, front liners, etc.). The advisory committee on immunization practices (ACIP) in the US recommended the priority list based on scientific evidence regarding COVID-19, ethical principles, and vaccination program logistics considerations (CDCMMWR 2020).

2.3 Multiple-objective decision-making models with GP

There have been several well-known management science methods for multiple-objective decision-making. Goal programming (GP) is one of the most widely applied solution techniques for decision problems that involve multiple and conflicting objectives. GP represents a special case of mathematical programming techniques, which can be used to achieve optimal satisficing solutions for multiple goals. The concept of GP was first introduced by Charnes et al. (1955). The solution algorithm of GP and its first use as a decision analysis tool were described in the seminal works by Lee (1972). Ignizio (1976) and Romero (1991) further explored extensions of GP. Schniederjans (1995) provided an overview of GP models, relationships between GP and other management science techniques, practical recommendations for GP model formulations and solutions, as well as a comprehensive bibliography of GP-related studies. Jones and Tamiz (2002) presented an annotated bibliography of GP applications and wrote a textbook (Jones and Tamiz 2010) with a specific focus on the practical applications of GP models. More recently, Colapinto et al. (2017) provided a comprehensive state-of-the-art review of GP applications in engineering, management, and social sciences.

GP models have been successfully used to improve perishable inventory management (Kendall and Lee 1980a) and better optimize healthcare resources (Jones and Tamiz 2010). Other studies that inspired this work include minimizing the stay in surgical patient wait-lists (Arenas et al. 2002), prioritizing subgroups during vaccine distribution programs (Hovav and Herbon 2017), optimizing the eradication of Ebola (Yu et al. 2015), a multidisciplinary approach for controlling global

infectious diseases (Silal, 2021), and managing perishable medical resources such as blood (Kendall and Lee 1980b). In this paper, the popular Excel's Solver was used to solve the proposed GP model. This study also used the methodologies proposed by Asllani and Lari (2015) and Asllani and Halstead (2015) that applied 0–1 GP models to reach various customer segments based on "recency–frequency–monetary value" (RFM) marketing approaches.

3 Developing a GP model

3.1 Population segmentation for vaccine distribution

Medical research considers age to be an especially important risk factor for contracting and recovering from COVID-19 (Davis et al. 2020). The CDC guidelines indicate that the risk for severe illness from COVID is much higher for people in their 60 s or older than those in their 40 s or 50 s (CDC 2020). Data support these claims—the top 30 countries with the largest percent of infections and especially deaths were countries that have older population (*eur.who.int*). Adults over 65 years of age represent 80% of hospitalizations and have a 23-fold greater risk of death than those under 65 (Muller et al. 2020). While people who are 65 years of age or younger and without underlying preexisting conditions have very small risks of COVID-19 death, even in pandemic epicenters (Ioannidis et al. 2020).

For this paper, the cutoff points were used to assign individuals into various age segments, as shown in Table 1. Studies indicate that individuals under 50 years of age are mostly asymptomatic to COVID (Jung et al. 2020; Spiegelhalter 2020); thus, they have low mortality risk. However, because this group carries the virus unknowingly most of the time, they also have the highest risk of infecting other people (Pollock and Lancaster 2020). Other age groups are considered less risky for spreading the virus since they usually show symptoms, and as such, are more likely tested and if necessary are quarantined.

Table 2 shows the cutoff points regarding the number of medical conditions. The conditions used in this study include diabetes, COPD, asthma, hypertension or other cardiovascular conditions, or obesity. In the first group, we placed people with no prior conditions. In the second group, those individuals with one or two conditions from the above list were placed, and so on. Data show that people with severe conditions have higher mortality rates (Kim et al. 2020). For example, 8 out of 10 deaths are for individuals with at least one condition, especially those with cardiovascular

Table 1 Population groups by age

Age	A-score	Mortality risk	Spread risk
0–49	1	Low	High
50–64	2	Average	Average
65–74	3	High	Low
75 and above	4	Very high	Very low

Table 2 Population groups by medical conditions

Number of medical conditions	M-score	Mortality risk	Spread risk
0	1	Very low	Average
1–2	2	Low	Average
3–4	3	Average	Average
5–6	4	High	Average
7 or more	5	Very high	Average

disease, hypertension and diabetes, and other chronic underlying conditions (euro. who.int 2020). There is no indication that either group has a higher risk of spreading the virus. As such, it was assumed that they all spread the disease at the "average" level.

Table 3 describes four groups of individuals according to their profession and their impact on the economy. Essential workers are those who conduct operations and services that are critical to continue operations and activities of critical infrastructure (healthcare; law enforcement, public safety, first responders; food and agriculture; energy; etc.) (Rho et al. 2020). The essential workers group exhibits the highest risk level for both getting infected and spreading the virus to the rest of the population. The other three groups are as follows: at-home individuals with a very low risk of spreading the virus, those who work from home but occasionally visit the workplace with a low risk of spreading the virus, and students and teacher who have a high risk of spreading the disease. An "average" mortality risk was assigned to each group.

3.2 Priorities for the vaccination campaign

Ideally, when a sufficient amount of vaccine is available and there is no urgency to reach the herd immunity level, vaccination priorities must be assigned based on the A-score, M-score, and O-score illustrated in the previous section. The groups with a higher score should be vaccinated first. However, this order may not be feasible when demand exceeds supply or if the vaccination program changes its goals or priorities. Under such system constraints, the vaccination campaign goal would be to decide which subgroups to vaccinate at any given time to achieve the priority goals. The following general priorities were incorporated in the prototype model:

Table 3 Population groups by occupation

Occupation	O-score	Mortality risk	Spread risk
At home individuals	1	Average	Very low
Online workers	2	Average	Very low
Students and teachers	3	Average	Average
Essential workers	4	Average	Very high

- P_1 = Comply with CDC and state guidelines for vaccinating based on certain age, medical condition, and occupation groups at a given time.
- P_2 = Minimize the spread of the virus to avoid overutilization of hospital capacities
- P3 = Minimize the mortality rate among COVID infected individuals.

The values of P_1, P_2, and P_3 illustrate the relative importance of these priorities. The set of priorities can be based on preemptive weights (i.e., $P1 >>> P2 >>> P3$) or on numerical weights. The relative importance of the priorities, either in terms of preemptive or numerical weights, can be assessed by healthcare experts and vaccination campaign managers. These priorities may need to be modified overtime as the pandemic mitigation conditions change such as the increased availability of FDA-approved vaccines, new variants of the virus that extend the capacity of the healthcare sector to a breaking point, the waning patience of people with COVID-associated restrictions, and the like.

Since it may not be possible to reach all the goals simultaneously, a set of penalties associated with not achieving the goals should be established. The penalty values would depend on the importance of reaching goals for different population segments. A new set of variables s_1, s_2, and s_3 can be created to represent the failure to meet each goal and the model can seek to minimize these variables accordingly. The important characteristic of the proposed GP model for COVID vaccine distribution is its robustness which accommodates modifications of goal priorities, variables, and parameters based on the changing environmental conditions.

3.3 Model formulation

3.3.1 Notations of the optimization models

$i = 1... A$—an index used to identify the individuals in a given age group (A-group).

$j = 1... M$—an index used to identify individuals in a given medical condition group (M-group).

$k = 1... O$—an index used to identify the individuals in a given economic impact group (O-group).

N_{ijk}—number of individuals who are in A-group i, M-group j, and O-group k.

N—the population size, where:

$$N = \sum_{i=1}^{A} \sum_{j=1}^{M} \sum_{K=1}^{O} N_{ijk}$$

r_{ijk}—the risk of infection, or the average number of new infections that an individual in A-group i, M-group j, and O-group k can cause if not vaccinated.

d_{ijk}—the mortality rate of individuals who are in A-group i, M-group j, and O-group k.

V—the number of available vaccines.

3.3.2 Decision variables

Let the decision variables be 0–1 unknown variable as follows:

$x_{ijk} = 1$ if individuals in A-group i, M-group j, and O-group k are vaccinated; 0, otherwise

$$Minimize\ Z = P_1 s_1^- + P_2 s_2^+ + P_3 s_3^+ \tag{1}$$

subject to:

$$\sum_{i=1}^{A}\sum_{j=1}^{M}\sum_{k=1}^{O} N_{ijk}x_{ijk} + s_1^- - s_1^+ = 0\ i\ \in\ \{1...A\}, j\ \in\ \{1...M\}, k \in \{1...O\} \tag{2}$$

$$\sum_{i=1}^{A}\sum_{j=1}^{M}\sum_{k=1}^{O} r_{ijk}N_{ijk}(1-x_{ijk}) + s_2^- - s_2^+ = 0 \tag{3}$$

$$\sum_{i=1}^{A}\sum_{j=1}^{M}\sum_{k=1}^{O} d_{ijk}x_{ijk} + s_3^- - s_3^+ = 0 \tag{4}$$

$$\sum_{i=1}^{A}\sum_{j=1}^{M}\sum_{k=1}^{O} N_{ijk}x_{ijk} \leq V \tag{5}$$

$$x_{ijk} = 0\ or\ 1, \forall i, j, k \tag{6}$$

$$s_p^+ \geq 0,\ s_p^- \geq 0\ where\ p = 1, 2, or\ 3 \tag{7}$$

Equation (1) is the objective function. It seeks to minimize the deviational variable s_1^-, s_2^+, and based on previously established priorities P s_3^+ $_1$, P_2, and P_3. For example, if $P_1 = 1$, $P_2 = 5$, and $P_3 = 10$, then the model will first minimize s_3^+ as such ensuring the minimization of mortality rate is given the top priority (with priority 10), then the model will minimize s_2^+ to ensure the number of new infections remains low (with priority 5). Finally, the model will minimize s_1^- ensuring that required subgroups are vaccinated (with priority 1).

Equation (2) is a deviational constraint and represents the vaccination requirement of certain population subgroups. For example, at any given time, the decision-maker must ensure that individuals above a certain age or individuals with a certain number of medical conditions must be vaccinated as required by CDC or state guidelines. Thus, the right-hand side (RHS) value represents the number of people that belong to certain age and medical conditions that must be vaccinated according to the CDC guidelines, while the triple summation on the left side of the equation represents the number of people from these subgroups who are vaccinated. By minimizing the negative deviation s_1^- (seeking to achieve $s_1^- = 0$),

the model seeks to maximize this number of individuals from these subgroups who receive the vaccine.

Equation (3) represents the risk of spreading the virus. If $x_{ijk} = 1$, then individuals in A-group i, M-group j, and O-group k are vaccinated, as such the risk of infections is zero $(1 - x_{ijk} = 0)$. Otherwise, the risk of spreading the disease is r_{ijk}. By minimizing the positive deviation s_2^+ and possibly making it zero, the model seeks to suggest a solution that will minimize the spread of the virus. Equation (4) is also a deviational constraint that represents the mortality rate. By minimizing the positive deviation s_3^+ and possibly making it zero, the model seeks a solution that will minimize the mortality rate. Equation (5) is a system constraint that ensures that the sum of the vaccines assigned to each A-group i, M-group j, and O-group k does not exceed the number of available vaccines (V). Finally, Eq. (6) enforces binary values to the decision variables (x_{ijk}), and Eq. (7) enforces non-negativity values to the positive deviational variables (s_p^+) as well as negative deviational variables (s_p^-).

4 Results

4.1 Descriptive analytics for population segments

This study used a dataset of 545,760 individual records from kaggle.com (Mukherjee 2020) to illustrate the proposed prototype model. Among other variables, this dataset has information about age, medical conditions, and whether the individual survived the Covid-19 infection or not. We used that information to calculate the number of individuals in each A-group i and M-group j. The data file, however, does not contain any records on the occupation; therefore, we used general demographics (Rho et al. 2020) to assign individuals in O-group k.

Tables 4, 5, and 6 summarize information for age, medical conditions, and occupation group, respectively. Table 4 organizes the population sample based on age-cutoff suggested in Table 1. Thus, the first row represents all individuals from 0 to 49 years old, and for identification purposes, A-score of 1 was assigned to this group. Because it is assumed, as previously discussed, that this group is most likely to spread the virus (since they are mostly asymptomatic), the highest risk score of

Table 4 Descriptive analytics based on age

Age cutoff	A-score	Risk of spread	Survival rate	Number of individuals
0	1	4	0.9800	365,464
50	2	3	0.8916	121,066
65	3	2	0.7613	35,983
75	4	1	0.7083	23,247
			Total	545,760

Table 5 Descriptive analytics based on the number of medical conditions

Number of medical conditions cutoff	M-score	Survival rate	Number of individuals
0	1	0.9552	279,883
1	2	0.9389	193,072
3	3	0.8625	61,400
5	4	0.7358	10,712
7	5	0.7128	693
		Total	545,760

Table 6 Descriptive analytics based on the occupation

Occupation categories	O-score	Risk of spread	Number of individuals
At home	1	1	109,432
Online	2	1	54,448
Student or teacher	3	3	218,446
Essential	4	5	163,434
		Total	545,760

four was assigned to this group. In the dataset, there were 365,464 individuals in this age group. Using the model, the survival rate for this group was calculated to be at 0.9800. The same calculations were made for the other age groups.

In Table 5, the population sample is organized based on the number of medical conditions of individuals. The first row represents all individuals that have no medical conditions. An M-score of 1 was assigned to this group. In the dataset, there were 279,883 individuals in this group. The second row represents the individuals with 1 or 2 medical conditions; the third row represents individuals with 3 or 4 medical conditions, and so on. Using the model, the survival rate for all groups of medical conditions was calculated.

Table 6 shows the population sample organized based on occupation. The population sample (as discussed earlier, see Table 3) was classified into four categories: at-home individuals, online workers, students and teachers, and essential workers. A-score of 1 was assigned for at-home individuals. These individuals have a minimum risk of spreading the infection; therefore, a risk value of 1 was assigned. The same lowest risk value of 1 was assigned to those working from home during the pandemic. As for students and teachers that are considered a medium risk of spreading the virus, a risk value of 3 was assigned, and to essential workers that have the highest risk, a risk value of 5 was assigned.

In Table 7, a small sample of the dataset is presented to demonstrate how the proposed model was used to calculate the risk of spreading the disease and the mortality rate for individuals.

For example, suppose an individual in the first row is 27 years old, has no medical conditions, and is an essential worker. Using "vlookup" Excel

Table 7 The risk of spreading and mortality rate calculation for each individual

Individual ID	Age	MedCond	Occupation	A-score	M score	O score	Risk of spread based on age	Risk of spread based on occupation	Average spread risk	Mortality based on age	Mortality based on condition	Average mortality rate
50624012333	27	0	Essential	1	1	4	4	5	4.5000	0.019991	0.0447650	0.0324
99500564132	41	0	Essential	1	1	4	4	5	4.5000	0.019991	0.0447650	0.0324
99400080298	58	4	At home	2	3	1	3	1	2.0000	0.108395	0.1374919	0.1229
99400080288	41	1	Essential	1	2	4	4	s	4.SOOO	0.019991	0.0611171	0.0406
99400080278	25	0	At home	1	1	1	4	1	2.5000	0.019991	0.0447650	0.0324
99400080268	42	1	At home	1	2	1	4	1	2.5000	0.019991	0.0611171	0.0406
99400080258	16	0	Student or teacher	1	1	3	4	3	3.5000	0.019991	0.0447650	0.0324
99400080248	61	2	Student or teacher	2	2	3	3	3	3.0000	0.108395	0.0611171	0.0848
99400080238	68	1	At home	3	2	1	2	1	1.5000	0.238724	0.0611171	0.1499
99400080228	12	1	Student or teacher	1	2	3	4	3	3.5000	0.019991	0.0611171	0.0406
99400080218	41	0	Student or teacher-	1	1	3	4	3	3.5000	0.019991	0.0447650	0.0324
99400080208	7	0	Student or teachet	1	1	3	4	3	3.5000	0.019991	0.0447650	0.0324
99400080198	78	0	At home	4	1	1	1	1	1.0000	0.291694	0.0447650	0.1682
99400080188	38	2	Online	1	2	2	4	1	2.5000	0.019991	0.0611171	0.0406
99400080178	41	2	Essential	1	2	4	4	5	4.5000	0.019991	0.0611171	0.0406
99400080168	48	0	At home	1	1	1	4	1	2.5000	0.019991	0.0447650	0.0324
99400080158	13	0	At home	1	1	1	4	1	2.5000	0.019991	0.0447650	0.0324
99400080148	34	0	Onllne	1	1	2	4	1	2.5000	0.019991	0.0447650	0.0324
99400080138	33	0	Student or teacher-	1	1	3	4	3	3.5000	0.019991	0.0447650	0.0324

functions, A (age)-score of 1 to this person, M (medical condition)-score of 1, and O (occupation)-score of 4 were assigned. Similarly, the individual's risk of spreading the virus is 4 based on age (see Table 4) and 5 based on occupation (see Table 6). Thus, the average risk is 4.5. The mortality rate based on the individual's age is 1–0.98001 = 0.01999 (see Table 4), and the mortality rate based on the number of medical conditions is 1–0.955235 = 0.044765 (see Table 5). Thus, the mortality rate for this individual is 0.0324.

Table 8 shows the initial values of the model parameters that we used in our illustration. It is assumed that the available doses of vaccines are less than the number of individuals who need vaccination; specifically, 54,576 vaccines can only cover 10% of the total number of individuals (545,760). It is also assumed that CDC or state government guidelines require that individuals older than 65 years of age and those with three or more medical conditions must be vaccinated as soon as possible.

Figure 1 presents a screenshot of the objective function, constraints, and decision variables. The model has a total of 80 binary decision variables and six non-binary deviational variables. As mentioned earlier, there are three priorities, which, for illustration purposes, were assigned an initial value $P1 = P2 = P3 = 5$. The figure also shows the (aforementioned) constraints: three deviational constraints (2), (3), and (4), and one system (5) constraint. The initial values of the decision variables are zero.

4.2 GP model solutions

To show the efficiency and sensitivity of the proposed prototype model, three scenarios were run. In the base scenario, equal priorities were used to verify the model's feasibility and identify and explain the solution. Then, two additional scenarios were tried. Scenario 1 prioritized avoiding the risk of spreading the virus, and Scenario 2 prioritized the goal of minimizing the mortality rate.

4.2.1 Base scenario: equal priorities vaccination program

This is the scenario when goal priorities are the same ($P1 = P2 = P3$). This solution where the priorities are given equal weights is shown in Fig. 2. As shown, the

Table 8 Model parameters

% of vaccine availability	10%
Number of available vaccines	54576.00
Number of individuals to be vaccinated	545760.00
Number of vaccinated individuals	0.00
Number of subgroups with individuals that are older than 65 and with more than 3 medical conditions to be vaccinated	26912.00
Number of vaccinated individuals older than 65 and with more than 3 medical conditions	0.00
Total amount of spread risk	0.00
Total amount of mortality rate	0.00

Priorities							
P1: Age and Medical Condition	1						
P2: Spread of Virus	1						
P3: Mortality	1						
(1) Minimize Z=	0						
	Actual Level	Negative Dev	Positive Devi	LHS		RHS	
Age and Medical Condition (2)	0.00	0.00	0.00	0.00 =		26912.00	
Spread of Virus Constraint (3)	0.00	0.00	0.00	0.00 =		0.00	
Mortality Rate Constraint (4)	0.00	0.00	0.00	0.00 =		0.00	
Vaccine Availabilty Constraint (5)	0.00	0.00	0.00	0.00 =		54576.00	

				Age			
				0-49	50-64	65-74	above 75
At Home	Number of Medical Conditions	0		0.00	0.00	0.00	0.00
		1-2		0.00	0.00	0.00	0.00
		3-4		0.00	0.00	0.00	0.00
		5-6		0.00	0.00	0.00	0.00
		7 or above		0.00	0.00	0.00	0.00
Online	Number of Medical Conditions	0		0.00	0.00	0.00	0.00
		1-2		0.00	0.00	0.00	0.00
		3-4		0.00	0.00	0.00	0.00
		5-6		0.00	0.00	0.00	0.00
		7 or above		0.00	0.00	0.00	0.00
Student or Teacher	Number of Medical Conditions	0		0.00	0.00	0.00	0.00
		1-2		0.00	0.00	0.00	0.00
		3-4		0.00	0.00	0.00	0.00
		5-6		0.00	0.00	0.00	0.00
		7 or above		0.00	0.00	0.00	0.00
Essential	Number of Medical Conditions	0		0.00	0.00	0.00	0.00
		1-2		0.00	0.00	0.00	0.00
		3-4		0.00	0.00	0.00	0.00
		5-6		0.00	0.00	0.00	0.00
		7 or above		0.00	0.00	0.00	0.00

(Occupation labels the rows: At Home, Online, Student or Teacher, Essential)

Fig. 1 Decision variables, objective function, and constraints

model suggests that everyone older than 65 and those with more than three medical conditions must be vaccinated. This requirement satisfies the first priority goal ($s_1^- = 0.00$) that meets the CDC guidelines. One possible explanation of this "unexpected compliance" is that Solver, in a search for continuous improvement, tends to start at this feasible solution and moves away from that only if it finds a better solution, which is unlikely since the three priorities have equal weights. Therefore, the rest of the available vaccines are distributed "randomly, without a specific goal" to other groups, since the goal priorities are the same.

As expected, the solution in Fig. 2 will not change if the first priority was enhanced, since the constraint is already satisfied. The other priorities, the spread of the virus ($s_2^+ = 57.00$), and the mortality rate ($s_3^+ = 6.37$) are not achieved. This result demonstrates the proposed model's ability to evaluate whether certain vaccination guidelines will help achieve the vaccination program goals regarding mortality rate, herd immunity, and hospital utilization.

4.2.2 Scenario 1: minimizing the virus spread risk

In this scenario, to make sure that the virus spread risk is minimized, the value of $P2$ was increased to 1000. As shown in Fig. 3, the vaccination policy recommended in this scenario lowered the positive deviation of the spread of risk constrain from 57.00 to11.50, a reduction of 79.82%. A very significant

Priorities						
P1: Age and Medical Condition	1					
P2: Spread of Virus	1					
P3: Mortality	1					
(1) Minimize Z=	63.37485485					
	Actual Level	Negative Dev	Positive Devi	LHS		RHS
Age and Medical Condition (2)	26912.00	0.00	0.00	26912.00 =		26912.00
Spread of Virus Constraint (3)	57.00	0.00	57.00	0.00 =		0.00
Mortality Rate Constraint (4)	6.37	0.00	6.37	0.00 =		0.00
Vaccine Availabilty Constraint (5)	54576.00	0.00	0.00	54576.00 =		54576.00

Occupation	Category	Number of Medical Conditions	Age 0-49	50-64	65-74	above 75
	At Home	0	0.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	1.00	1.00
		5-6	0.00	0.00	1.00	1.00
		7 or above	0.00	0.00	1.00	1.00
	Online	0	1.00	1.00	1.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	1.00	1.00
		5-6	0.00	0.00	1.00	1.00
		7 or above	0.00	0.00	1.00	1.00
	Student or Teacher	0	0.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	1.00	1.00
		5-6	0.00	1.00	1.00	1.00
		7 or above	0.00	0.00	1.00	1.00
	Essential	0	0.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	1.00	1.00
		5-6	0.00	0.00	1.00	1.00
		7 or above	0.00	0.00	1.00	1.00

Fig. 2 Initial solution with equal GP priorities

improvement. This solution offers another positive result as a "byproduct." The mortality rate is also reduced from 6.37 to 1.34, that is, a reduction of 78.96%. However, this solution indicates that not all the subgroups could not be reached: those aged above 65 or those with more than three medical conditions since the negative deviation is not zero ($s_1^- = 16{,}373.00$).

4.2.3 Scenario 2: minimizing the mortality rate

As mentioned in the previous section, increasing the weight on the second priority already contributed significantly to the reduction of the mortality rate. As such, the values of $P1 = 1$, $P2 = 1000$, and $P3 = 1000$ are kept. As shown in Fig. 4, there is a further reduction in the mortality rate. s_3^+ value drops to 1.03 in this scenario from 6.37 in the base scenario, consisting of 83.83% reduction. This solution represents the best scenario regarding the mortality rate. However, it should be noted that according to this scenario, the goal of vaccinating the individuals according to age or the number of medical conditions is less achievable since the "Age and Medical Condition" constraint's negative deviation increases from zero in the base scenario to 17,476.00. The same is true regarding the "Risk of Spread" goal where the positive deviation increased from 11.50 to 12.00.

Priorities						
P1: Age and Medical Condition	1					
P2: Spread of Virus	1000					
P3: Mortality	1					
(1) Minimize Z=	27874.34069					
	Actual Level	Negative Dev	Positive Devi	LHS		RHS
Age and Medical Condition (2)	10539.00	16373.00	0.00	26912.00	=	26912.00
Spread of Virus Constraint (3)	11.50	0.00	11.50	0.00	=	0.00
Mortality Rate Constraint (4)	1.34	0.00	1.34	0.00	=	0.00
Vaccine Availabilty Constraint (5)	54576.00	0.00	0.00	54576.00	=	54576.00

Occupation		Number of Medical Conditions	Age			
			0-49	50-64	65-74	above 75
At Home		0	1.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	1.00	1.00
		5-6	0.00	0.00	1.00	1.00
		7 or above	0.00	0.00	0.00	0.00
Online		0	0.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	1.00	0.00
		5-6	0.00	0.00	0.00	0.00
		7 or above	0.00	0.00	0.00	0.00
Student or Teacher		0	0.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	1.00	0.00
		5-6	0.00	0.00	0.00	0.00
		7 or above	0.00	0.00	0.00	0.00
Essential		0	0.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	0.00	0.00
		5-6	0.00	0.00	0.00	0.00
		7 or above	0.00	0.00	0.00	0.00

Fig. 3 Solution with GP priorities ($P1 = 1$, $P2 = 1000$, $P3 = 1$)

5 Discussion and conclusion

As COVID-19 vaccines have become available, government officials are struggling with their efforts to administer the vaccines in the population's arms as quickly as possible. At the time this paper was being prepared, the proportion of the US population fully vaccinated was about 66.14% (with states ranging from 50.71% to 92.84%) (Johns Hopkins University 2021). Timely distribution of the vaccines is the key to achieving herd immunity, and there is a sense of urgency as new strains of the virus that are extremely contagious have evolved. Besides the speed of delivery, the state-run vaccination programs have multiple goals. These goals include reducing the number of new infections, minimizing the mortality rate, while at the same time following the CDC guidelines regarding people's age, medical conditions, and occupation. This paper offers a decision-making tool that allows federal and local government officials and healthcare practitioners to determine the optimum COVID vaccine distribution based on age, medical condition, and occupation. The proposed GP model seeks to satisfy three objective criteria: prioritize the elderly and those with medical conditions, minimize the virus spread, and minimize the mortality rate. The model used binary values, and its solution indicates which specific set of population subgroups must be vaccinated at a given time.

The first step in the modeling process is identifying the cutoff points for each group. This paper used cutoff points based on the COVID-19-related information

Priorities						
P1: Age and Medical Condition	1					
P2: Spread of Virus	1000					
P3: Mortality	1000					
(1) Minimize Z=	30508.4932					
	Actual Level	Negative Dev	Positive Devi	LHS		RHS
Age and Medical Condition (2)	9436.00	17476.00	0.00	26912.00	=	26912.00
Spread of Virus Constraint (3)	12.00	0.00	12.00	0.00	=	0.00
Mortality Rate Constraint (4)	1.03	0.00	1.03	0.00	=	0.00
Vaccine Availabilty Constraint (5)	54576.00	0.00	0.00	54576.00	=	54576.00

Occupation		Number of Medical Conditions	Age			
			0-49	50-64	65-74	above 75
	At Home	0	1.00	0.00	0.00	1.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	0.00	1.00
		5-6	0.00	0.00	0.00	0.00
		7 or above	0.00	0.00	0.00	0.00
	Online	0	0.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	0.00	0.00
		5-6	0.00	0.00	0.00	0.00
		7 or above	0.00	0.00	0.00	0.00
	Student or Teacher	0	0.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	1.00	1.00
		5-6	0.00	0.00	0.00	0.00
		7 or above	0.00	0.00	0.00	0.00
	Essential	0	0.00	0.00	0.00	0.00
		1-2	0.00	0.00	0.00	0.00
		3-4	0.00	0.00	0.00	1.00
		5-6	0.00	0.00	0.00	0.00
		7 or above	0.00	0.00	0.00	0.00

Fig. 4 Solution with GP Priorities ($P1 = 1$, $P2 = 1000$, $P3 = 1000$)

available at the time of this study. However, specific criteria and their cutoff points should be determined based on the unique conditions of the area (city, state, country, or region) in collaboration with medical personnel and healthcare policy makers. The key contribution of this research is that it proposes a dynamic model that allows the decision-makers to change the objective criteria (beyond grouping on age, medical condition, and occupation), create additional or fewer subgroups based on changes in the environment, and adjust variables as the vaccination program moves throughout different stages. This paper illustrated the model and its efficiency using a large dataset of real-world COVID-19, which includes more than a half-million individuals. The paper demonstrates that the proposed GP model can significantly improve the outcome of a vaccination program, especially for decreasing the mortality rate.

The specific results of this study should not be used to recommend or provide guidelines on vaccination programs as the prototype model assumed a certain set of environmental conditions, which could be different from those of real-world scenarios or environments. However, the greatest advantage of the proposed GP model is that it demonstrates how a continuous evaluation of the priorities of various goals to determine and adjust the vaccine distribution plans can be done based on the fluid and dynamic environmental conditions. Furthermore, this dynamic GP model can be adjusted or refined for different levels (national, regional, state, city/county, etc.)

and for different timelines (e.g., the first dose, second dose, etc.). The vaccination campaign is now well under way in many countries. However, the proposed model can be used by countries at different stages of vaccination, for the distribution of new vaccines for new COVID variants, and for the preparation of future pandemics. The 0–1 GP model can accurately predict the subgroups of individuals to be vaccinated. The real efficacy of the model is its capability for dynamic change and scalability based on the unique conditions of the decision environment. The model can also adjust the optimization criteria according to the goals or subgoals of the vaccination campaign's priorities. Another easy modification to the model is changing the decision variable requirements from binary to continuous. In such cases, the solutions would indicate what proportion of individuals in each subgroup needs to be vaccinated, instead of determining whether a subgroup must be vaccinated or not.

Finally, because each pandemic has its own characteristics, a decision support model should be flexible enough for assigning appropriate priorities to different population segments depending on changing environmental conditions or vaccine distribution logistics requirements. For example, the Spanish Flu of 1918–1920 was deadly for young people as compared to COVID-19 which has been especially dangerous to the older generation. The proposed model is capable of handling such challenges in managing vaccine distribution for future pandemics.

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