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A Mixed-Integer Programming Model for Optimal Allocation of COVID-19 Vaccines in Davao City

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Abstract

With the emergence of COVID-19 in Davao City, the need to acquire herd immunity through vaccination is paramount in averting the further spread of the disease in addition to complying with health and safety protocols. This study presents a reformulation of Smalley et al.'s (2015) oral cholera vaccine—mixed-integer programming model (OCV-MIP) to fit the context of the COVID-19 vaccination campaign in the city for 5 years, with consideration of the possible need for annual revaccination, given limited supply and budget resources, to minimize COVID-19 cases further. The population is divided into subgroups with associated incidence rates serving as the basis for the optimal allocation of vaccines. Different ways of population stratification by some combinations of risk areas and age group divisions were explored. The results revealed that it is optimal to prioritize the vaccination of subgroups with the highest incidence rates.

Keywords: forecasting · COVID-19 · Davao City · LINGO · Mixed-Integer Programming · Optimization · Philippines · SARS-CoV-2 · Vaccinet

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A Mixed-Integer Programming Model for Optimal Allocation of COVID-19 Vaccines in Davao City

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Introduction

The Coronavirus Study Group of the International Committee on Taxonomy of Viruses officially recognized the virus from Wuhan City, Hubei Province of China as the Severe Acute Respiratory Syndrome Coronavirus 2 or SARS-CoV-2 (Gorbalenya et al. 2020), while the disease caused by this particular virus is called the COVID-19 (World Health Organization 2020). The SARS-CoV-2 surfaced around late November of 2019 in China (Morens et al. 2020) where it was suspected to have emerged from an animal-to-human transmission, as the case with the previously studied coronaviruses SARS-CoV and MERS-CoV (Shi et al. 2020).

The alarming spread of SARS-CoV-2 has caused the world to suffer another horrendous tragedy—the COVID-19 pandemic. The probable long-term solution to prevent more infections is mass vaccination (Schaffer DeRoo et al. 2020). Given the formulation of the new COVID-19 vaccines in its early phase as well as the potential rise of new variants, the world's next step is to vaccinate a significant proportion of its entire population, securing community immunity. With limited vaccine supply at the start of the pandemic, there is a need to plan its distribution and allocation for efficient results.

In the global context, COVID-19 vaccine allocation optimization models have been utilized by a few authors since the pandemic emerged. The vaccine allocation models of González-Parra et al. (2022), Shim (2021), Matrajt et al. (2021), Scroggins et al. (2022), Mak et al. (2022), Miura et al. (2021), and Han et al. (2021) classified the population into smaller groups according to their age, since a difference in the severity impact of COVID-19 among these subgroups is deemed possible. These studies motivate the current study's exploration of the optimal vaccine allocation in a city differentiated by age groups within each risk area. Gonzalez-Parra et al. (2022), Han et al. (2021), and Shim (2021) formulated age-structured compartmental models of the COVID-19 dynamics to understand how vaccines should be optimally distributed within the population. Specifically, Gonzalez-Parra et al. (2022) utilized two nonlinear models, while Shim (2021) and Han et al. (2021) applied their deterministic models to South Korea and China, respectively. Matrajt et al. (2021) also used an age-structured mathematical model of the COVID-19 dynamics elevated with the integration of an optimization algorithm to extract the optimal vaccine allocation strategy in a pandemic. Miura et al. (2021) also focused on utilizing an optimization algorithm to solve the same problem in the Netherlands. Scroggins et al. (2022) focused on spatial optimization by assigning a mobility measure of people per locality to decide how vaccines should be allocated. A recurring objective among the optimization models of Shim (2021), Scroggins et al. (2022), Miura et al. (2021), and Han et al. (2021) is the minimization of new infections among the population. Meanwhile, Buckner et al. (2021) emphasized the presence of a limited vaccine supply in the first few months of the vaccination campaigns. Moreover, Tavana et al. (2021) considered a location-inventory problem for temperature-sensitive COVID-19 vaccines while Mak et al. (2022) studied the inventory dynamics of the vaccine rollout process then evaluated the efficacy of different vaccine allocation strategies through an SEIR model.

With COVID-19 in the Philippines, studies have been carried out focusing on formulating optimization models to minimize further deaths and prevent further cases from skyrocketing. The study of Buhat et al. (2021) and Miñoza et al. (2021) used linear programming models for minimizing further cases and deaths, simulating the country's COVID-19 scenario based on the optimization results. These studies, however, have not considered classifying the population into age groups and particular risk areas in a population as well as the case of revaccination. Additionally, only case prevalence, as opposed to case incidence rates, was explored. Hence, these gaps motivated this study to adopt and employ some modifications to the OCV-MIP model of Smalley et al. (2015) and apply it in Davao City, Philippines. Smalley et al. (2015) explored a mixed-integer programming model for the optimization of oral cholera vaccine allocation over multiple periods using incidence rates to minimize further infections. They then utilized the model for the Bangladesh Cholera scenario. The model was formulated to consider a population stratified by age groups and risk regions.

Davao City, a highly urbanized city in Mindanao, is the commercial center of Southern Mindanao (National Economic and Development Authority 2021). The city, comprising 182 *barangays*, has a total population of 1,866,401 as of 2021 (World Population Review 2021). According to the Philippine Information Agency in Davao Region, the detected COVID-19 cases during its early phase were coming from work or health facilities while the rest was traced from the New Davao Matina Gallera cockpit, which accelerated the local transmission in the city (Revita 2020). Since then, community quarantines have been imposed on the locality in the hopes of containing the disease's spread. Lockdowns were then imposed on several *puroks* (the smallest recognized geographical unit in the Philippines) in Barangay 23-C and Purok 8 of Barangay 21-C by the City Government of Davao due to a disturbing rise of COVID-19 cases (Ornedo 2020). Last July 2020, Barangay 23-C was considered as a hotspot of COVID-19 transmission as they experienced an alarming increase in case incidence (Llemit 2020). Consequently, Davao City was reported to be among the 18 high-risk localities in the Philippines (Gonzales 2020). As of 24 March 2021, the acting head of the Davao City Health Office (CHO) has reported that COVID-19 cases were becoming prevalent even in the outskirts of the downtown area. Among the critical risk areas identified were Mintal and Subasta (Calinan), while *barangays* (the smallest recognized administrative division in the Philippines) such as Barangay 10-A, Communal, R. Castillo, and Toril Proper were classified as high-risk areas. According to the report, people living in those areas and traveling to the downtown area for errands and business purposes probably have contracted the disease, thus providing an avenue for increased community transmission in the outskirts (Llemit 2021). Consequently, the city has undergone several COVID-19 surges brought on by the emergence of COVID-19 variants. With the disease not yet eliminated as of this manuscript's writing, a future COVID-19 surge is still a possibility.

Hence, the study aims to explore the optimal COVID-19 vaccine allocation for the Davao City population stratified by age groups and risk areas. The findings of the study may be used by health program officers and basis for the policymakers to design an optimal vaccination rollout.

Materials and Methods

Flowchart of the Methodology. The performed methodology is illustrated in Figure 1. It contains the steps taken to accomplish the set objectives of the study.

The study aims to determine an optimal COVID-19 vaccine allocation among various age groups per risk area in Davao City for 5 years (2021–2025) such that further cases are kept to a minimum. Specifically, the study aims to: (1) reformulate the mixed-integer programming model of Smalley et al. (2015) to minimize the number of cases throughout the city and (2) collect estimate values for the parameters involved in the optimization model. Moreover, the study aims to observe the optimal vaccine allocation whenever (a) the population is stratified by age groups only, (b) risk areas only, and (c) age groups and risk areas (comparative analysis).

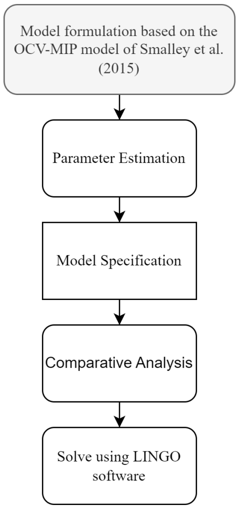

FIGURE 1 Flowchart of the methodology

Modeling Approach

The Oral Cholera Vaccine–Mixed-Integer Programming (OCV-MIP) model of Smalley et al. (2015) was modified and utilized in the study. The current model considered 4 different age groups (20–29 years, 30–39 years, 40–49 years, and 50–59 years) within each risk area in Davao City to determine an optimal annual COVID-19 vaccine allocation over 5 years.

Risk area and age group classification. Davao City *barangays* were classified into 4 risk areas namely: critical-risk, high-risk, moderate-risk, and low-risk. The classification was based on the 2015 senior citizens (ages 60 years or older) population proportion concerning the total population. For the study, the risk area classification was based on the set criteria in Table 1. The reasoning behind the risk area classification according to the elderly population proportion is that the elderly are observed to be at a higher risk of mortality due to COVID-19 (World Health Organization Regional Office for Europe 2020).

The risk areas are then further classified by the following age groups: (1) 20–29 years, (2) 30–39 years, (3) 40–49 years, and (4) 50–59 years. The age groups only accommodate ages 20–59 years old since the current study focused only on the context of mass vaccination, specifically, the priority eligible group C as classified by the Department of Health (DOH) in their Interim Plan (DOH 2021a). Since there are (4) risk areas and f4 age groups, a total of 16 subgroups exist.

TABLE 1 Risk area classification in terms of elderly population proportion

Elderly proportion	Risk classification
[0,0.02)	Low-risk area
[0.02,0.04)	Moderate-risk area
[0.04,0.08)	High-risk area
[0.08,0.08+)	Critical-risk area

Model Formulation

Tables 2 – 4 summarize the sets of indices, the parameters, and the decision variables included in the empirical model formulation.

TABLE 2 Sets of indices

Index Set	Description
L	Set of risk areas (Critical, High, Moderate, Low)
$\bar{G}_a$	Set of ages i in age group $a, \forall a \in A$
N	Set of vaccination years ={{1,2 ,...,12},{13,14,...,24},{25,26,...,36}, {37,38,...,48},{49,50,...,60}}
$\bar{G}_n$	Set of months t in vaccination year $n, \forall n \in N$

TABLE 3 Parameters

Parameter	Description
$P_{l,a,t}$	The population size of age group a, living in area l, in month t, $l \in L, a \in A, t \in \bar{G}_n, n \in N$
$\bar{P}_{l,i,n}$	The population size of age i, living in area l, in year n, $l \in L, i \in \{20,21,...,59\}, n \in N$
H	The percentage of people to be vaccinated among the total population
$I_{l,a}$	The base case incidence rate for age group a living in area $l, l \in L, a \in A$
E	Vaccine efficacy of two vaccine doses
$\hat{I}_{l,a}$	The calculated incidence rate among the vaccinated persons in age group a, living in area $l, l \in L, a \in A$
C_t	Vaccine (two doses) supply in year n, $n \in N$
B_n	Budget for the vaccination campaign in year n, $n \in N$
m	Cost of two vaccine doses

TABLE 4 Decision variables

Decision Variable	Classification	Description
$Y_{l,i,t}$	Primary decision variable	Number of newly vaccinated persons in month t, of age i, living in area l, $l \in L, i \in \{20,21,22,\ldots,59\}, t \in \bar{G}_n, n \in N$
$V_{l,a,t}$	Secondary decision variable	Number of newly vaccinated persons in month t, in age group a, living in area l, $a \in A, l \in L, t \in \bar{G}_n, n \in N$
$X_{l,a,t}$	Secondary decision variable	The incidence rate for persons in age group a, living in area l, during month t, $l \in L, a \in A, t \in \bar{G}_n, n \in N$

The following reformulated models are grounded by the following assumptions:

1. The population is delimited to the city residents that are between 20–59 years old.
2. The population still increases annually (using the assumed annual growth rates) but is assumed constant across the 12 months per year.
3. Barangays are classified into 4 risk areas according to their proportion of the elderly population.
4. The 1–year case incidence report from 15 March 2020 to 14 March 2021 provides a decent estimate of the incidence rates throughout the 5 years considered.
5. The calculated incidence rates are constant for all subgroups throughout the 5 years considered.
6. The monthly supply is assumed constant for the first 5 months of the first year. The monthly supply increases by 100% by the sixth month of the first year and remains constant until 2025 since it is the most realistic scenario.

The main MIP model formulation is given as follows.

$$\text{Minimize} \quad \sum_{l \in L} \sum_{a \in A} \sum_{t \in \bar{G}_n, n \in N} P_{l,a,t} X_{l,a,t} \qquad [1]$$

Subject to the following constraints:

$$\sum_{l \in L} \sum_{a \in A} V_{l,a,t} \leq C_t \qquad ,\forall t \in G_n, n \in N \qquad [2]$$

$$\sum_{l \in L} \sum_{a \in A} \sum_{t \in \bar{G}_n} m \cdot V_{l,a,t} \leq B_n \qquad ,\forall n \in N \qquad [3]$$

$$\sum_{12(n-1) < t \leq 12n} Y_{l,i,t} \leq \bar{P}_{l,i,n} \qquad ,\forall n \in N, l \in L, i \in \{20,21,\ldots,59\} \qquad [4]$$

$$V_{l,a,t}, Y_{l,i,t} \in \mathbb{Z}^+ \qquad ,\forall i, l \in L, a \in A, t \in \bar{G}_n, n \in N \qquad [5]$$

where,

$$X_{l,a,t} = I_{l,a} \frac{V_{l,a,t}}{P_{l,a,t}} + \left(1 - \frac{V_{l,a,t}}{P_{l,a,t}}\right) \hat{I}_{lat} \qquad ,\forall l \in L, a \in A, t \in \bar{G}_n, n \in N \qquad [6]$$

$$V_{l,a,t} = \sum_{i \in \bar{G}_a} Y_{l,i,t} \qquad ,\forall l \in L, a \in A, t \in \bar{G}_n, n \in N \qquad [7]$$

The objective function holds the summation of the case incidence per subgroup given their specific case incidence rates. The optimization model aims to minimize the prevalence of further cases in the total population considered. The constraints represent the resources available such as the limited monthly vaccine supply and the annual vaccination campaign budget. Moreover, the last constraint guarantees that the annual total vaccinated population will not exceed the total population.

Model Specification

The model formulation presented above is revised accordingly to fit the scenarios to be explored under the comparative analysis.

Comparative analysis. This section compares the resulting model outputs from scenarios of age group-risk area stratification, age-group-only, and risk-area-only. The reformulations of the main MIP model are discussed below.

The age-group-only model reformulation consists of the same structure as that of the original model, however, the indices for risk areas are removed. For the parameter values, the modified population (per age group) are expressed as the sum of the population of a particular age group across all risk areas. The incidence rates were calculated as well using the same formula previously shown while noting the age-group-only stratification.

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$$\text{Minimize} \quad \sum_{a\in A} \sum_{t\in\bar{G}_n, n\in N} P_{a,t} X_{a,t} \qquad [8]$$

Subject to the following constraints:

$$\sum_{a\in A} V_{a,t} \le C_t \qquad ,\forall t\in\bar{G}_n, n\in N \qquad [9]$$

$$\sum_{a\in A} \sum_{t\in\bar{G}_n} m\cdot V_{a,t} \le B_n \qquad ,\forall n\in N \qquad [10]$$

$$\sum_{12(n-1)<t\le 12n} Y_{i,t} \le \bar{P}_{i,n} \qquad ,\forall n\in N, i\in\{20,21,\ldots,59\} \qquad [11]$$

$$V_{a,t,} Y_{i,t} \in \mathbb{Z}^+ \qquad ,\forall\ i, a\in A, t\in\bar{G}_n, n\in N \qquad [12]$$

where

$$X_{a,t} = I_a \frac{V_{a,t}}{P_{a,t}} + \left(1 - \frac{V_{a,t}}{P_{a,t}}\right)\hat{I}_a \qquad ,\forall a\in A, t\in G_n, n\in\bar{N} \qquad [13]$$

$$V_{a,t} = \sum_{i\in\bar{G}_a} Y_{i,t} \qquad ,\forall a\in A, t\in\bar{G}_n, n\in N \qquad [14]$$

The risk-area-only model reformulation consists of the same structure as that of the original model. However, the indices for age groups are removed. For the parameter values, the modified population (per risk area) are expressed as the sum of the population across all age groups in that particular risk area. The incidence rates were calculated using the same formula previously shown while noting the risk-area-only stratification. Also, the decision variable $Y_{l,i,t}$ is removed here since its purpose is to hold the vaccine allocation for each age *i*, which does not apply in this scenario as risk areas are the only stratification considered.

$$\text{Minimize} \quad \sum_{l\in L} \sum_{t\in\bar{G}_n, n\in N} P_{l,t} X_{l,t} \qquad [15]$$

Subject to the following constraints:

$$\sum_{l\in L} V_{l,t} \le C_t \qquad ,\forall t\in G_n, n\in N \qquad [16]$$

$$\sum_{l\in L} \sum_{t\in\bar{G}_n} m\cdot V_{l,t} \le B_n \qquad ,\forall n\in N \qquad [17]$$

$$\sum_{12(n-1)<t\le 12n} Y_{l,t} \le \bar{P}_{l,n} \qquad ,\forall n\in N, l\in L \qquad [18]$$

$$V_{l,t,} Y_{l,t} \in \mathbb{Z}^+ \qquad ,\forall l\in L, t\in\bar{G}_n, n\in N \qquad [19]$$

where

$$X_{l,t} = I_l \frac{V_{l,t}}{P_{l,t}} + \left(1 - \frac{V_{l,t}}{P_{l,t}}\right)\hat{I}_l \qquad ,\forall a\in A, t\in\bar{G}_n, n\in N \qquad [20]$$

LINGO Codes

Each of the model formulations was translated into a LINGO code following the software's set-based modeling language. The LINGO code for the main MIP, the age-group-only, and risk-area-only are displayed in Appendix [1]–[3] of the supplementary material.

Obtaining the Parameter Values

The collected data for the study were from the most recent sources available as of May 2021. Specifically, for the case incidence data, the observation period was from 15 March 2020 to 14 March 2021. The vaccine supply parameter estimation was based on the March to May 2021 record from the city government. Moreover, the 2015 population data per *barangay* and age group were utilized in the study. The dataset served as the basis for the necessary population projections for the consequent years considered.

Population projections. The necessary data for the initial population of Davao City per age for every risk area was obtained from the website of Humanitarian Data Exchange (2021). The Philippines - Subnational Population Statistics dataset was explored, with the specific file named phl_admpop_2015_5yr.xlsx, of size 11.8 Mb. Since the available data only reveals the 2015 population per subgroup, projections were generated for the estimated population until the year 2020 using a constant annual growth rate of 2.30% (Philippine Statistics Authority 2017). Also, the population was considered constant throughout 12 months. Furthermore, the consecutive annual population projections for the years 2021 until 2025 were estimated based on the annual growth rate in Davao City as reported by World Population Review (2021) as shown in Table 5.

TABLE 5 Estimated growth rates

Year	Estimated growth rate (%)[a]
2020	2.30[b]
2021	2.24
2022	2.21
2023	2.18
2024	2.16
2025	2.16

[a] Lifted from World Population Review (2021)
[b] Lifted from Philippine Statistics Authority (2017)

Let the annual growth rate be denoted by $g_y, y \in \{2021,2022,2023,2024,2025\}$. The following formula was used for the population projection per risk area l and age i:

$$P_{l,i,y+1} = P_{l,i,y}\,(1+g_y). \qquad [21]$$

Base case incidence rates. For each of the subgroups, the base case incidence rates were calculated from the gathered confirmed cases" with derived from the confirmed COVID-19 cases. These values tell how fast a subgroup gets infected with the virus. To estimate the base case incidence rate, the following formula was used, as discussed by LaMorte (2016):

$$\hat{I}_{lat} = \frac{\sum_{w=1}^{365} N_w}{\sum_{w=1}^{365} N_w \cdot w + \left(S_{l,a} \sum_{w=1}^{365}\right) \cdot 366}. \qquad [22]$$

The new cases in day w is denoted by N_w, and $S_{l,a}$ denotes the total susceptible population of subgroup (under risk area l age group a) at the start of the observation period. The value for $S_{l,a}$ is equal to the projected population per subgroup in 2020. The observation period considered is from 21 March 2020 to 20 March 2021 (a total of 365 days). For the risk-area-only and age-group-only models, the base case incidence rates are also calculated accordingly. Specifically, for the risk-area-only model, the case counts were summed up first by risk areas then formula [22] of LaMorte (2016) was utilized to calculate $\hat{I}_l$ for the 4 risk areas. Similarly, this procedure was followed to calculate the base case incidence rates $\hat{I}_a$ for the age-group-only model.

Case incidence rates. Given a vaccine efficacy of E and the base incidence rate $\hat{I}_{l,a}$ the case incidence rate for the vaccinated persons was calculated as follows:

$$\hat{I}_{l,a} = (1- E)\hat{I}_{l,a}. \qquad [23]$$

The vaccine efficacy that is assumed in the model is equal to the mean efficacy of the vaccines that were initially planned to be procured. In Davao City, AstraZeneca, Pfizer, Sinovac, and Sputnik V (City Government of Davao 2021a) are the vaccines currently procured. The reported efficacy of these vaccines is 70.4%, 95%, 51%, and 91.6% (DOH 2021b). Hence, the assumed constant vaccine efficacy E for the study is 0.77.

Monthly vaccine supply. In the model, a parameter C_t represented the vaccine supply for each year considered. Based on the 4-month record, from 1 March to 4 July 2021, around 150,160 complete vaccine doses were administered (City Government of Davao 2021b). Hence, the estimated value of this parameter C_t is 37,540. However, the parameter can take on a different value as the supply of vaccine doses may increase over time through the pandemic.

Annual budget. The cost of a vaccine dose was estimated by taking the mean price of vaccine doses to be procured in the city, namely, AstraZeneca, Pfizer, Sinovac, and Sputnik V (City Government of Davao 2021a). In the study, a parameter B_n held the assumed annual vaccination budget for the population considered where it is equal to the product of the cost of two vaccine doses and the target population to vaccinate to achieve herd immunity.

Software used. To solve the mixed-integer programming model, the LINGO 19.0 solver was utilized. LINGO is an optimization modeling software built to solve problems such as linear, nonlinear, and integer, stochastic programming problems in a fast and efficient manner. The software employs an intuitive way of formulating models and equations. Datasets from spreadsheets can be easily imported into the software while the outputs generated by the built-in solvers in LINGO can also be displayed in the spreadsheets for ease of presentation (LINDO Systems, Inc. 2003).

Results and Discussion

Parameterization

Obtaining the model solution necessitated some parameter values that were gathered from the website of the City Government of Davao, DOH Regional Office, and Humanitarian Data Exchange, among others. Some parameters, and consequently some variables, were calculated and rescaled beforehand. The parameter values are shown in Appendix Tables 1–9 in the supplementary material.

Main MIP Model Solution (Age Group andRisk Area Stratification)

Translating the empirical model into a LINGO code and importing the encoded parameter values from Excel, the optimal solutions were obtained after executing the codes in the software. The solution report for the main MIP model was also recorded. The optimal solutions were then exported to the set ranges in Excel using the @ OLE function in LINGO.

According to the main MIP model, to reduce the number of projected infections over 5 years to 50054.91 (Appendix 4 in the supplementary material), it is optimal to prioritize the vaccination of all subgroups under the critical-risk areas, then under the moderate-risk areas, and High-1, High-2, and High-4. The prioritization follows the order of the incidence rates, that is, the subgroups with higher incidence rates assume a higher rank in the prioritization.

Figure 2 illustrates this optimal prioritization, where most of the population among the critical-risk and moderate-risk areas are suggested to be vaccinated (represented by the blue bars) since their corresponding incidence rates (represented in orange and gray bars) were higher compared to the other subgroups. On the other hand, the 5 subgroups, namely, Low-1, Low-2, Low-3, Low-4, and High-3, received no vaccine allocations for the main MIP model. This is caused by their relatively low incidence rates and the assumed low supply of vaccines. Since the model prioritizes subgroups with the highest incidence rates first, even though High-3 and Low-1 had corresponding non-zero incidence rates, these two subgroups have the second to the lowest incidence rates. Hence still no allocation was provided. The subgroups Low-2, Low-3, and Low-4 reported no incidence rates, which may be because of the underreporting of cases, especially at the start of the pandemic.

The stacked area chart in Figure 3 and table of values (see Appendix Table 10 in the supplementary material) show the optimal solution for the main MIP model, that is, the population to vaccinate (by hundreds) per subgroup.

The numbers, 1, 2, 3, and 4, right after the risk areas represent the age groups 20–29, 30–39, 40–49, and 50–59 years, respectively. Specifically, the subgroup LOW-1 corresponds to the 20–29 years age group under the low-risk area.

The risk areas are represented in specific color gradients where the low-risk areas are represented in blue gradient, moderate-risk areas in yellow gradient, high-risk areas in orange gradient, and critical-risk areas in black gradient. The age groups under each risk area are represented in different shades of the specific color gradient of the risk area where the lightest shade represents the youngest age group (20–29 years) and the darkest shade for the oldest age group (50–59 years).

Given the budget allocation set and the ample supply of vaccines assumed by the start of the sixth month, 70% of the considered population will be fully vaccinated by the end of every year for all 5 years considered as shown in Table 6. The associated costs of each annual vaccination campaign are also listed in the table. In Davao City, the set goal is to vaccinate about 70% of its population, which is equivalent to 1,299,894 people (Infosoft 2022). The city's first 12 months of the vaccination campaign, from March 2021 to

February 2022, fully vaccinated 1,264,857 people (City Government of Davao 2022), which led to the achievement of 97.43% of the herd immunity goal (equivalent to vaccinating only 68.11% of the entire city's population), considering that the vaccine supply already boosted a few months since the start of the city's campaign. Perhaps the city was not able to fully exhaust its available supply because the number of new vaccinees did not persist to rapidly increase as well. However, as of February 2022, the city continues its campaign and even aims to vaccinate 80% or more of its population as the vaccine supply allows (City Government of Davao 2022). Several studies cited factors affecting the low turnout of vaccinees. According to Khairat et al. (2022), in the United States of America, the hesitancy to accept COVID-19 vaccines was driven by the people's low confidence in the formulated vaccines, the prevalence of apprehensions about their side effects, and the general distrust in the government. In a survey done in Portugal by Soares et al. (2021), factors such as a young age, mistrust in the vaccine and the government's COVID-19 pandemic response, and lack of knowledge of the safety and efficacy of the vaccines, are revealed to affect vaccine hesitancy. Hence, the government must extend the necessary information about the safety of the vaccines to the public even more and, more importantly, take the pandemic response more seriously.

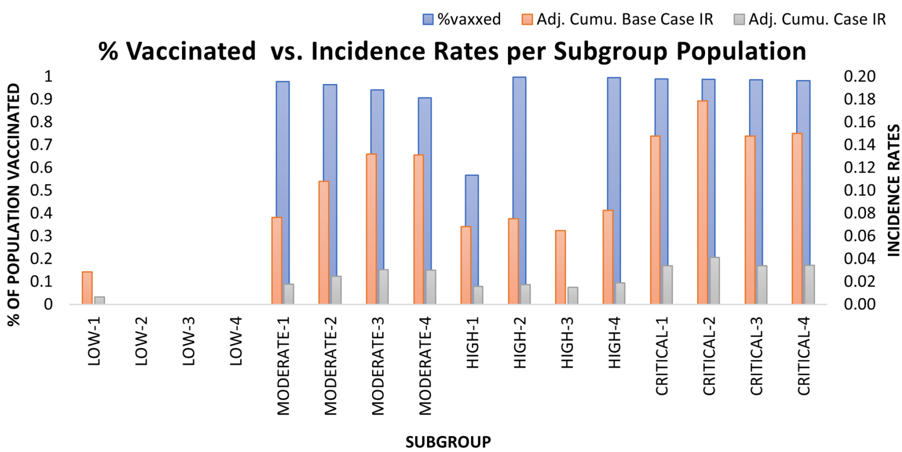

FIGURE 2 Percentage of the vaccinated population versus incidence rates per subgroup

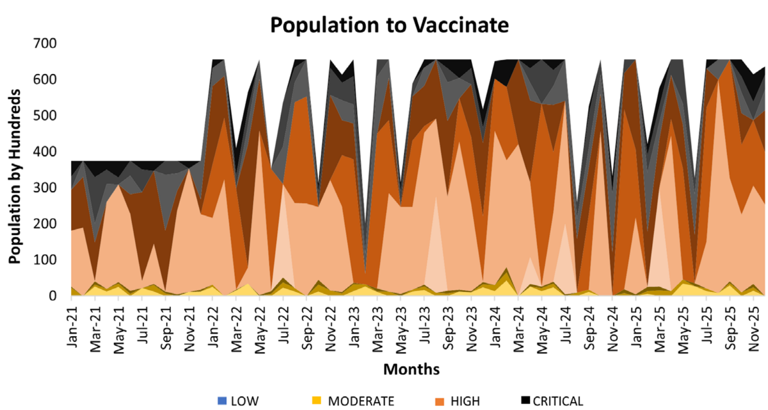

FIGURE 3 The optimal solution for the main MIP model

TABLE 6 Summary of the vaccination campaign cost

Year	People to vaccinate	Projected population	Herd immunity achieved?	Total cost (PhP)
2021	687,500	982,159	Yes	1,347,242,187.50
2022	702,600	1,003,793	Yes	1,376,832,525.00
2023	717,900	1,025,595	Yes	1,406,814,787.50
2024	733,300	1,047,678	Yes	1,436,993,012.50
2025	749,000	1,070,023	Yes	1,467,759,125.00

Comparative Analysis

In this section, the population is stratified by age groups only (for the age-group-only model) and by risk areas only (for the risk-area-only model). The corresponding model solutions and objective function values are then compared to explore how to best stratify the considered population.

Age-group-only model. Translating the empirical model into a LINGO code and utilizing the same supply and budget values along with some specific population and incidence rates values (see Appendix Tables 3–4 and 7 in the supplementary material), the optimal solutions were obtained after executing the codes in the software. The solution report for the age-group-only model was also recorded.

According to the solution report (see Appendix 5 in the supplementary material), the objective function value is 50186.45, that is, the number of projected COVID-19 cases for the considered population (20–59-year-olds) over 5 years. The age-group-only model prioritizes the age groups 30–39, 20–29, then 50–59, and lastly the 40–49-year-olds (see Appendix Figure 1 in the supplementary material). The actual number of people to vaccinate per age group is shown in Appendix Table 11 of the supplementary material. Observe the base case incidence rates (and consequently case incidence rates) of the age groups in Figure 4 and notice that the prioritization of allocations coincides with the order of the incidence. The higher the incidence associated with an age group, the higher up is the group in the priority list.

Risk-area-only model. Executing the LINGO code and utilizing the same supply and budget values along with some specific population and incidence rates values (see Appendix Table 5 and 8 in the supplementary material), the solution report for the risk-area-only model was also recorded.

According to the solution report (see Appendix 6 in the supplementary material), the objective function value is 48323.59, that is, the number of projected COVID-19 cases for the considered population (20–59-year-olds) over 5 years. The risk-area-only model only prioritizes the critical-risk area (see Appendix Figure 1 in the supplementary material). The actual number of people to vaccinate per risk area is shown in Appendix Table 12 in the supplementary material. Observe the base case incidence rates (and consequently case incidence rates) of the risk areas in Figure 5 and notice that the critical-risk area is characterized by the highest incidence rates followed by the moderate-risk, high-risk, and low-risk areas.

The numbers 1, 2, 3, and 4, right after the risk areas represent the age groups 20–29, 30–39, 40–49, and 50–59 years, respectively. Specifically, the subgroup LOW-1 corresponds to the 20–29 years age group under the low-risk area.

After executing the codes for the three models under comparative analysis, it was revealed that classifying the population in terms of risk areas performed best in terms of minimizing the number of cases as shown in Table 7. Consequently, the model classifying the population into both risk areas and age groups yielded lesser case counts than the model characterized by age groups only. This may be explained by the existence of a significant difference in the incidence rates of specific risk areas. However, focusing on the age groups only, no clear pattern in the incidence rates arises—different age groups appear to assume nearly similar incidence rates (see Figure 4 and 5). In the incidence rates per subgroup (Figure 6), any age group may have more cases in a particular risk area but lesser cases in another. However, any risk area follows an order in terms of incidence rates even across different age groups. Since the goal is to minimize further infections, it is optimal to divide the population by risk areas and then vaccinate accordingly.

TABLE 7 Objective Function or Z values by distribution strategy for comparative analysis

Model	Objective function value, Z
Risk area and age group (main model)	50054.91
Risk-area-only	48323.59
Age-group-only	50186.45

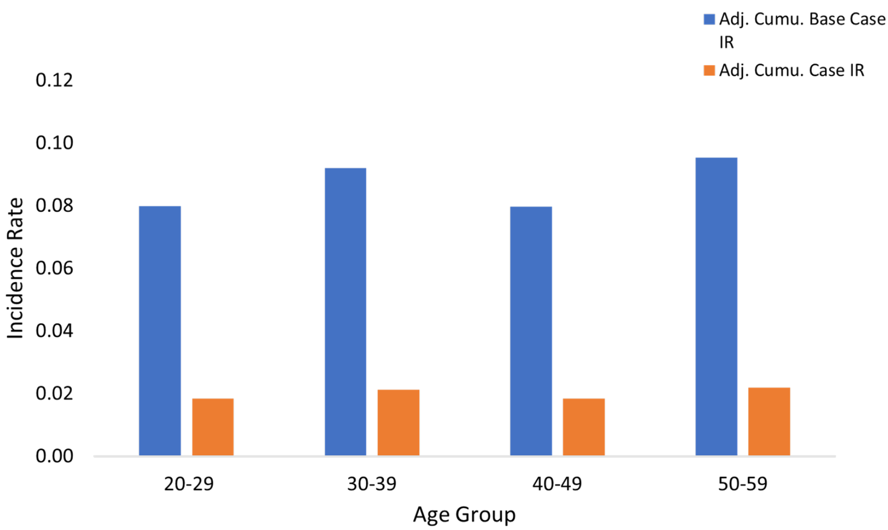

FIGURE 4 Adjusted cumulative incidence rates per age group

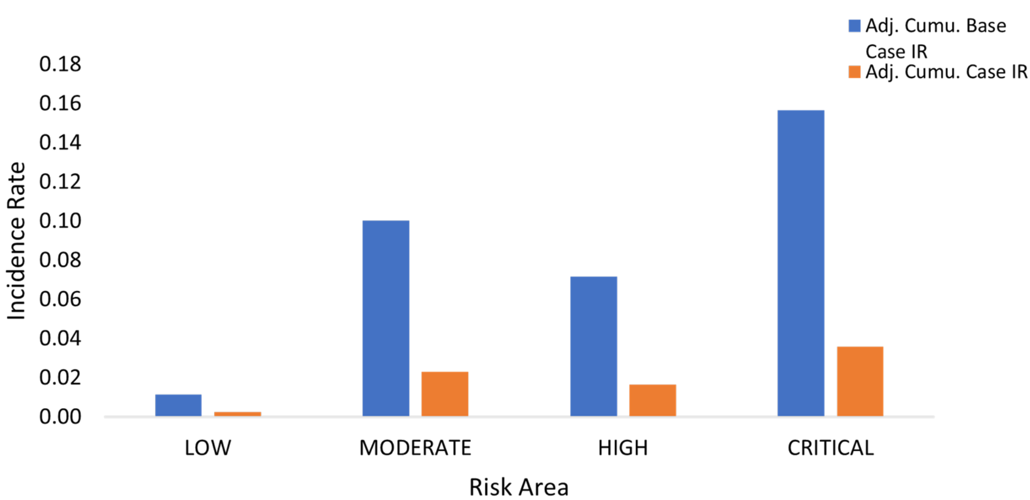

FIGURE 5 Adjusted cumulative incidence rates per risk area

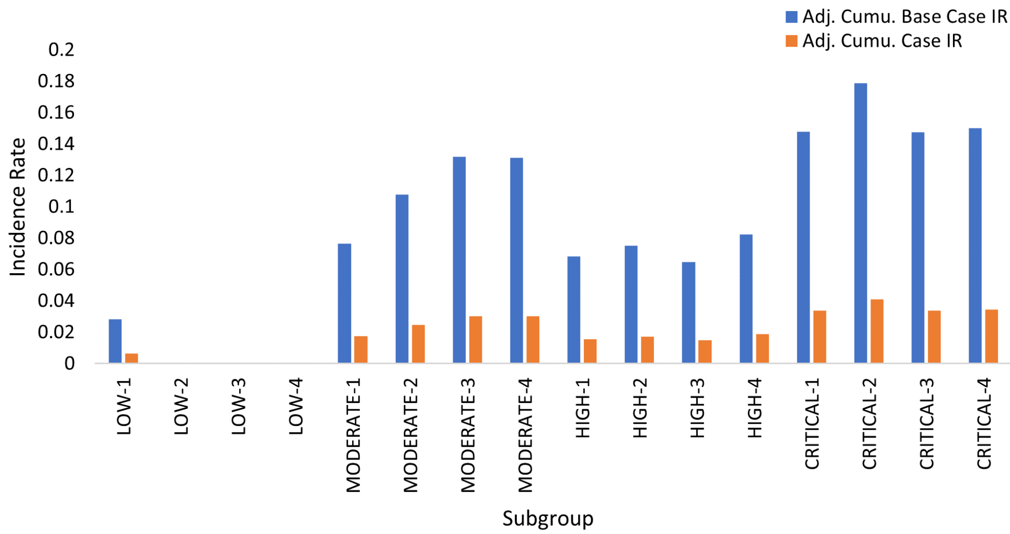

FIGURE 6 Adjusted cumulative incidence rates per subgroup

Conclusion and Recommendations

As the COVID-19 infection emerged as a pandemic spreading throughout the Philippines, the number of cases continues to increase. In the long term, mass vaccination is deemed to significantly avert further cases from spreading. This study aimed to determine an optimal COVID-19 vaccine allocation among age groups per risk area (subgroups) in the Davao City for 5 years (2021–2025) such that further cases are minimized. This study reformulated the MIP model of Smalley et al. (2015) to fit the city's context and determined the number of people vaccinated among the subgroups. A comparative analysis was performed where a simplified population stratification, either by age groups or by risk areas only, was assumed to determine which model outputs better optimal solutions.

The model solution mainly prioritizes the vaccination of the subgroups with the highest incidence rates. Also, it was found that stratifying the population solely by risk areas performed the best in terms of minimizing the projected number of cases, suggesting that age group stratification is insignificant.

With more vaccine supply, the model can allocate vaccines to more subgroups including those with low incidence rates, which were tagged by the model as the last in the prioritization. Moreover, given that the model is heavily reliant on the reported cases to approximate the COVID-19 incidence rates that consequently determines the vaccine allocation, much more significant results can be derived with more accurate reporting of cases per *barangay* level. Reflecting upon the model's performance in producing optimal vaccine allocations in the population, it is also paramount to note its limitation: the incidence rates are assumed to be constant for the entire 5 years and were calculated based on the recorded COVID-19 cases in the city for a year. Utilizing a longer period of observation as a basis to have a better estimate of the incidence rates for 5 years may be a point to consider since the incidence of COVID-19 may fluctuate over time as new variants proliferate or the other way around where cases may dissipate due to the possibility of the emergence of a more intensive response to control further infection spread.

Finally, the incorporation of the entire city's population in the 5-year vaccination campaign, considering the possibility of the utilization of specific vaccine brands to cater to the younger and the elderly, may be worth exploring. Also, it may be interesting to follow the prioritization for the vaccination of the health sector, the workers, and other groups outlined by the DOH where each group also has specific incidence rates separate from the masses, which were the ones considered in the current study. The integration of SEIR compartmental models into the vaccine allocation model, the use of dynamic population, and new data on the reported cases to update incidence rates can be explored.

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Notes

The supplementary material can be accessed through the link:
https://drive.google.com/file/d/1MiSZDE8KJI_p9FtFLZDbhPWD-7kzfZbM/view

References

Buckner JH, Chowell G, Springborn MR. 2021. Dynamic prioritization of COVID-19 vaccines when social distancing is limited for essential workers. Appl. Biol. Sci. https://doi.org/10.1073/pnas.2025786118

Buhat CAH, Lutero DSM, Olave YH, Quindala KM, Recreo MGP, Talabis DASJ, Torres MC, Tubay JM, Rabajante JF. 2021. Using constrained optimization for the allocation of COVID-19 vaccines in the Philippines. Appl Health Econ Health Policy. 19: 699–708. https://doi.org/10.1007/s40258-021-00667-z

City Government of Davao. 2021a. Mayor Inday Sara Duterte assures more vaccine to arrive for Dabawenyos. City Government of Davao City; [accessed 5.2.21]. https://www.davaocity.gov.ph/covid-19/mayor-inday-sara-duterte-assures-more-vaccine-to-arrive-for-dabawenyos/

City Government of Davao. 2021b. Fully vaccinated Dabawenyos now over 50k. City Government of Davao City; [accessed 7.13.21]. https://covid19.davaocity.gov.ph/fully-vaccinated-dabawenyos-now-over-50k/

City Government of Davao. 2022. Davao COVID-19 TF reiterates booster importances city aims to inoculate total population. City Government of Davao City; [accessed 4.23.22]. https://covid19.davaocity.gov.ph/davao-covid-19-tf-reiterates-booster-importance-as-city-aims-to-inoculate-total-population/

[DOH] Department of Health. 2021a. The Philippine National deployment and vaccination plan for COVID-19 vaccines: Interim plan; [accessed 5.2.21]. https://doh.gov.ph/sites/default/files/basic-page/The Philippine National COVID-19 Vaccination Deployment Plan.pdf

[DOH] Department of Health. 2021b. Know your vaccines (vaccine matrix: current evidence). Department of Health; [accessed 7.13.21]. https://doh.gov.ph/vaccines/know-your-vaccines

Gonzales C. 2020. 18 LGUs classified as COVID-19 high-risk areas — OCTA Research. Inquirer.Net; [accessed 5.26.21]. https://newsinfo.inquirer.net/1352948/18- lgus-classified-as-covid-19-high-risk-areas-octa-research

González-Parra GC, Cogollo MR, Arenas AJ. 2022. Mathematical Modeling to study optimal allocation of vaccines against COVID-19 using an age-structured population. Axioms 11: 109. https://doi.org/10.3390/axioms11030109

Gorbalenya A, Baker S, Baric R, de GrootR, Drosten C, Gulyaeva A, Haagmans B, Lauber C, Leontovich A, Neuman B, Penzar D, Perlman S, Poon L, SamborskiyD, Sidorov I, Sola I, Ziebuhr J. 2020. The species Severe acute respiratory syndrome-related coronavirus: classifying 2019-nCoV and naming it SARS-CoV-2. Nat. Microbiol. 5: 536-544. https://doi.org/10.1038/s41564-020-0695-z

Han S, Cai J, Yang J, Zhang J, Wu Q, ZhengW, Shi H, Ajelli M, Zhou XH Yu, H. 2021. Time-varying optimization of COVID-19 vaccine prioritization in the context of limited vaccination capacity. Nature Communications 12(1): 4673. https://doi.org/10.1038/s41467-021-24872-5

Humanitarian Data Exchange. 2021. Philippines - subnational population statistics. Humanitarian Data Exchange; [accessed 5.5.21]. https://data.humdata.org/dataset/5a466c38-32a2-47de-ba36-70530505df98

Infosoft. 2022. Davao City hits 94.35 % target herd immunity. COVID19 Davao City Gov; [accessed 4.23.22]. https://covid19.davaocity.gov.ph/davao-city-hits-94-35-target-herd-immunity/?msclkid=26166201c2c411ecb0b3a5de7a4137f2

Khairat S, Zou B, Adler-Milstein J. 2022. Factors and reasons associated with low COVID-19 vaccine uptake among highly hesitant communities in the US. American J Infect Control. 50(3): 262–267. https://doi.org/10.1016/j.ajic.2021.12.013

LaMorte WW. 2016. Measures of disease frequency. Boston University School of Public Health; [accessed 5.8.21]. https://sphweb.bumc.bu.edu/otlt/MPH-Modules/EP/EP713_DiseaseFrequency/EP713_DiseaseFrequency4.html

LINDO Systems, Inc. 2003. LINGO 19.0 - Optimization modeling software for linear, nonlinear, and integer programming. LINDO Systems, Inc.; [accessed 5.28.21]. https://www.lindo.com/index.php/products/lingo-and-optimization-modeling

Llemit RG. 2020. Davao City village under lockdown due to surge in Covid-19 cases. SunStar DAVAO; [accessed 5.15.21]. https://www.sunstar.com.ph/article/1862502/Davao/Local-News/Davao-City-village-under-lockdown-due-to-surge-in-Covid-19-cases

Llemit RG. 2021. Covid-19 cases 'spreading more in Davao City outskirts [WWW Document]. SunStar DAVAO; [accessed 5.16.21]. https://www.sunstar.com.ph/article/1889918/Davao/Local-News/Covid-19-cases 'spreading-more-in-Davao-City-outskirts

Mak HY, Dai T, Tang CS. 2022. Managing two-dose COVID-19 vaccine rollouts with limited supply: Operations strategies for distributing time-sensitive resources. Prod Oper Manag 31: 4424–4442. https://doi.org/10.1111/poms.13862

Matrajt L, Eaton J, Leung T, Brown E. 2021. Vaccine optimization for COVID-19: Who to vaccinate first? Sci. Adv. 7. https:// doi.org/10.1126/sciadv.abf1374

Miñoza JMA, Bongolan, VP, Rayo, JF. 2021. COVID-19 agent-based model with multi-objective optimization for vaccine distribution. arXiv. https://doi.org/10.48550/arXiv.2101.11400

Miura F, Leung KY, Klinkenberg D, Ainslie KEC, Wallinga J. 2021. Optimal vaccine allocation for COVID-19 in the Netherlands: A data-driven prioritization. PLoS Comput. Biol. 17(12). https://doi.org/10.1371/journal.pcbi.1009697

Morens DM, Breman JG, Calisher CH, Doherty PC, Hahn BH, Keusch GT, Kramer LD, LeDuc JW, Monath TP, Taubenberger JK. 2020. The origin of COVID-19 and why it matters. Am. J. Trop. Med. Hyg. 10: 955–959. https://doi.org/10.4269/ajtmh.20-0849

[NEDA] National Economic and Development Authority. 2021. Davao City. National Economic and Development Authority; [accessed 5.15.21]. https://nro11.neda.gov.ph/davao-region/davao-city/

Ornedo JM. 2020. Davao City locks down barangays after residents test positive for COVID-19. GMA News Online; [accessed 5.16.21].https://www.gmanetwork.com/news/news/regions/735027/davao-city-locksdown-barangays-after-residents-test-positive-for-covid-19/story/

[PSA] Philippine Statistics Authority. 2017. Davao Region population almost 4.9 million (results from the 2015 census of population). Philippine Statistics Authority; [accessed 5.1.21]. http://rsso11.psa.gov.ph/article/davao-region-population-almost-49-million-results-2015-census-population

Revita J. 2020. Cockpit in Davao City 'ground zero'. SunStar DAVAO; [accessed 4.18.23]. https://www.sunstar.com.ph/article/1851213/Davao/Local-News/Cockpit-in-Davao-City-ground-zero

Schaffer DeRoo S, Pudalov NJ, Fu LY. 2020. Planning for a COVID-19 Vaccination program. JAMA 323: 2458–2459. https://doi.org/10.1001/jama.2020.8711

Scroggins S, Goodson J, Afroze T, Shacham E. 2022. Spatial optimization to improve COVID-19 vaccine allocation. Vaccines. 11(1): 64. https://doi.org/10.3390/vaccines11010064

Shi Y, Wang G, Cai XP, Deng JW, Zheng L, Zhu HH, Zheng M, Yang B, Chen Z. 2020. An overview of COVID-19. J Zhejiang Univ Sci B. 21: 343–360. https://doi.org/10.1631/jzus.B2000083

Shim E. 2021. Optimal Allocation of the Limited COVID-19 Vaccine supply in South Korea. J. Clin. Med. 10(4): 591. https://doi.org/10.3390/jcm10040591

Smalley HK, Keskinocak P, Swann J, Hinman A. 2015. Optimized oral cholera vaccine distribution strategies to minimize disease incidence: A mixed integer programming model and analysis of a Bangladesh scenario. Vaccine. 33: 6218– 6223. https://doi.org/10.1016/j.vaccine.2015.09.088

Soares P, Rocha J, Moniz M, Gama A, Laires P, Pedro A, Dias S, Leite A, Nunes C. 2021. Factors associated with COVID-19 vaccine hesitancy. Vaccines 9(3): 300. https://doi.org/10.3390/vaccines9030300

Tavana M, Govindan K, Nasr AK, Heidary MS, Mina H. 2021. A mathematical programming approach for equitable COVID-19 vaccine distribution in developing countries. Annals of operations research: 1–34. https://doi.org/10.1007/s10479-021-04130-z

[WHO] World Health Organization. 2020. WHO Director-General's remarks at the media briefing on 2019-nCoV on 11 February 2020. World Health Organization; [accessed 4.29.21]. https://www.who.int/director-general/speeches/detail/who-director-general-s-remarks-at-the-media-briefing-on-2019-ncov-on-11-february-2020

World Health Organization Regional Office for Europe. 2020a. Statement – Older people are at highest risk from COVID-19, but all must act to prevent community spread. WHO Europe; [accessed 5.28.21]. https://www.who.int/europe/news/item/03-04-2020-statement-older-people-are-at-highest-risk-from-covid-19-but-all-must-act-to-prevent-community-spread

World Population Review. 2021. Davao City population 2021 [WWW Document]. World

Population Review; [accessed 5.10.21]. https://worldpopulationreview.com/world-cities/davao-city-population