Covid 19 vaccine order allocation: an optimization model with substitution

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Abstract

Purpose – This paper focuses on multi-objective order allocation with product substitution for the vaccine supply chain under uncertainty.

Design/methodology/approach – The weighted-sum minimization approach is used to find a compromised solution between three objectives of minimizing inefficiently vaccinated people, postponed vaccinations, and purchasing costs. A mixed-integer formulation with substitution quantities is proposed, subject to capacity and demand constraints. The substitution ratios between vaccines are assumed to be exogenous. Besides, uncertainty in supplier reliability is formulated using optimistic, most likely, and pessimistic scenarios in the proposed optimization model.

Findings – Covid-19 vaccine supply chain process is studied for one government and three vaccine suppliers as an illustrative example. The results provide essential insights for the governments to have proper vaccine allocation and support governments to manage the Covid-19 pandemic.

Originality/value – This paper considers the minimization of postponement in vaccination plans and inefficient vaccination and purchasing costs for order allocation among different vaccine types. To the best of the authors' knowledge, there is no study in the literature on order allocation of vaccine types with substitution. The analytical hierarchy process structure of the Covid-19 pandemic also contributes to the literature.

Keywords Order allocation, Covid-19 vaccine, Demand substitution, Mixed integer programming, Vaccine supply chain

Paper type Research paper

1. Introduction

A good vaccination plan requires setting a proper vaccine mix considering supplier reliability and vaccine efficacy to achieve herd immunity promptly. Vaccination plans are successful if supported by a reliable supply chain (Lemmens *et al.*, 2016). However, the preparation of vaccination plans is even more challenging when society is threatened by a pandemic such as the Covid-19 outbreak. Prompt and righteous decision-making becomes essential due to the emergency of the situation. In these uncertain environments, the central health authorities should make their plans to create a public immunity for a large part of the population as early as possible. The studies report that one person may infect two to four people on average, and 50 to 75% of the people would need to be resistant to reach herd immunity (Anderson and May, 1985; Randolph and Barreiro, 2020). Vaccination delivery performance and health center vaccination capacities are essential determinants of successful vaccination campaigns. However, the lockdowns, travel bans, and quarantine restrictions on suppliers cause massive disruptions to global supply chains, as in the case of the Covid-19 outbreak (Ivanov, 2020; Queiroz *et al.*, 2020). Besides, the pandemic raises uncertainty about the supply of medical equipment, consumables, effective therapies, and vaccinations (Koffman *et al.*, 2020).

Supplier selection and order allocation problems are considered jointly in the literature to achieve a cost-efficient and reliable plan to determine the order quantities. A traditional supplier selection for a commercial product involves the criteria such as prices, delivery rates, lead times, and several implied costs (Alejo-Reyes *et al.*, 2021). However, order allocation and supplier selection for a vaccine supply process, particularly in a pandemic, should consider vaccine efficacy and supplier reliability. Optimization models for the order allocation of commercial products mainly aim to minimize purchasing costs. However, there are other priorities to consider successfully solving a vaccine order allocation problem. This paper considers the minimization of postponement in vaccination plans and inefficient vaccination and purchasing costs for order allocation among different vaccine types. To the best of our knowledge, there is no study in the literature on the order allocation of vaccine types.

Order quantities assigned to vaccine suppliers are affected by vaccine substitutions. Allowing substitution between vaccine types is essential for minimizing postponing vaccinations, especially when one or more vaccines frequently become

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unavailable due to unreliable supplier delivery. Therefore, this study assumes that the other vaccines can substitute unavailable vaccine types according to specific substitution ratios. The problem of deciding which vaccine types should be purchased by considering their substitution ratios is similar to the product assortment problem in the literature. The product assortment problem is how to decide the order and inventory levels of a set of similar products by considering their market expectations and customers' preferences.

Governments prioritize the vaccination groups based on their age, health conditions, and societal roles (World Health Organization, 2021a). Though the community's health has the highest priority, governments should also consider their decisions' social and economic effects. Vaccine effectiveness, storage conditions, supplier reliability, community preferences, and many other factors substantially impact the speed of the vaccination process and affect society's health and economic welfare. Therefore, a government should evaluate this allocation problem from multiple perspectives to decide correct vaccine types and order quantities. The order allocation and vaccine substitution decisions are affected by the late and less than expected deliveries from suppliers, vaccination inefficacy, and the high cost of vaccine procurement. Therefore, the purchasing price is not the only objective since postponed and inefficient vaccinations significantly impact the success of an inoculation plan. This study develops a multi-objective optimization model for a vaccination plan that allows vaccine substitution to minimize purchasing costs and postponed and inefficient vaccinations. This paper proposes a weighted-sum approach to find an optimal solution to the multi-objective vaccine order allocation problem for different vaccine types. Analytical hierarchy process (AHP) is used to determine the weights of the objective functions by considering social, economic, and health-related factors. The objective functions of the multi-objective model are minimizing postponed and inefficient vaccination and purchasing costs. Postponement of vaccination results in late herd immunity, thus leading to more prolonged adverse effects on society and the health system. Using vaccine types with lower efficacy results in higher inefficient vaccination practices and negatively impacts herd immunity.

The main contributions of the study are threefold. First, the order allocation with vaccine substitution is introduced to the literature on the vaccine supply chain. Second, a vaccine order planning model with multiple objectives is developed and shown on an illustrative example for the Covid-19 pandemic. Third, the paper allows the buyer (government) to investigate the impacts of the suppliers' reliability on the vaccination plans and vaccine substitution rates on the postponed vaccinations.

The rest of the paper is structured as follows. Section 2 briefly reviews the literature. Section 3 and 4 present the problem definition, model development, and solution methodology. Section 5 provides an illustrative example and its results. Finally, Section 6 concludes the paper and discusses the future research directions.

2. Literature review

The COVID-19 outbreak has affected the global supply chains, where many global manufacturing companies experienced shortages due to the disruptions in their supply networks (Mchopa *et al.*, 2020). In their study on vaccine supply chains, Duijzer *et al.* (2018) classified the literature from the product, production, allocation, prioritization, and distribution perspective. Malmir and Zobel (2021) recently summarized the relief distribution and network optimization literature. They suggested a new sustainable humanitarian supply chain model involving transportation, delivery, equity, and deprivation costs. Rather than logistic costs, Malmir and Zobel (2021) emphasized the importance of proper calculation of the deprivation costs to reduce the suffering of affected people from Covid-19. Shirazi *et al.* (2021) and Zokaee *et al.* (2016) also developed optimization models for plasma supply for the pandemic of Covid-19 and relief chains, respectively. Borriello *et al.* (2021) investigated the Covid-19 vaccine characteristics that influence the preference of Australian citizens. Their study showed that the vaccine priorities changed according to the severity of the side effects of vaccines. Thompson and Anderson (2021) mainly evaluated the responses to the Covid-19 pandemic in the US and provided future research perspectives for the resilience of humanitarian supply chain and logistics management.

The vaccine order allocation decisions are also crucial for humanitarian supply chains. Various studies address the optimal order allocation strategy with a single objective using mathematical programming (Kaur and Singh, 2021; Esmaeili-Najafabadi *et al.*, 2019; Yang *et al.*, 2010). Developing a mixed integer program (MIP), Kaur and Singh (2021) proposed a multi-stage supplier selection and order allocation model under disruption risks. Two or more conflicting goals have also been studied in the order allocation problems using multi-objective optimization models (Jia *et al.*, 2020; Moheb-Alizadeh and Handfield, 2019; Mafakheri *et al.*, 2011; Songhori *et al.*, 2011). In their study to decide the location of disaster logistics hubs, Maharjan and Hanaoka (2018) suggested a fuzzy factor rating system to identify the objectives' weights in a multi-objective optimization problem. Gutjahr and Nolz (2016) summarized the studies on multi-criteria optimization in humanitarian aid and pointed out the rising usage of multi-criteria optimization in humanitarian decision-making problems.

Stochastic programming models have been proposed to deal with uncertainty and disruption risks in humanitarian supply chains (Vahidi *et al.*, 2018; Hosseini *et al.*, 2019). In a plasma supply chain designed to collect plasma from the newly recovered Covid-19 patients, Shirazi *et al.* (2021) developed a stochastic optimization modeling approach to locate blood collection sites and allocate plasma processing facilities. Similarly, Kenan and Diabat (2022) modeled the blood supply chain for the Covid-19 pandemic using stochastic programming under both demand and supply uncertainty. Under uncertain demand and supply processes, Zokaee *et al.* (2016) considered a humanitarian logistic relief chain consisting of suppliers, distribution centers, and affected areas. For optimum vaccine allocation, Yin and Büyüktahtakın (2022) developed a multi-stage stochastic programming model considering the uncertainty of the vaccine supply and the disease transmission rates. Their findings suggest that isolation is the most efficient way to slow down disease transmission, and vaccine acceptance rates only affect optimal vaccine allocation at the early stages under a tight vaccine supply.

Both multi-objective and stochastic programming models were also used together in the extant literature. Proposing a stochastic bi-objective mixed-integer programming model, Hosseini *et al.* (2019) developed a decision-making support tool to determine how to utilize proactive and reactive strategies in order allocation problems. Yenice and Samanlioglu (2020) developed a stochastic multi-objective mathematical model to identify the aid storage locations and distribution channels for the shelters in an earthquake relief network. Three earthquake scenario-specific objectives were solved simultaneously using the normalized weighted sum method in the model. Both Fathollahi-Fard *et al.* (2018) and Ramezani *et al.* (2013) designed a supply chain network using a multi-objective stochastic programming model. Fathollahi-Fard *et al.* (2018) considered both economic and social dimensions of a closed-loop supply chain network with four conflicting goals. For forward/reverse supply chain networks with some uncertain parameters, Ramezani *et al.* (2013) generated a set of Pareto-optimal solutions for three supply chain-related objective functions. Similarly, Jamali *et al.* (2021) employed a stochastic multi-objective mathematical model to configure a relief logistics network with three pillars of sustainability under the different injury severities. Aggarwal and Singh (2015) modeled multi-objective supplier selection problem under a stochastic environment and solved it using non-preemptive goal programming and the weighted aggregate function technique.

Metaheuristics were also utilized in the literature to solve the order allocation problem. Alejo-Reyes *et al.* (2021) developed a new heuristic for supplier selection and order allocation and compared it with two well-known meta-heuristics: particle swarm optimization and differential evolution. The sustainability in supplier selection and order allocation has also been addressed. For instance, Moheb-Alizadeh and Handfield (2019) developed a multi-objective mixed-integer linear programming model to allocate order quantities considering supplier selection and sustainability. Jia *et al.* (2020) included CO_2 emissions in the sustainability of the supplier selection and order allocation decisions.

Consumers usually consider buying another brand within a product category if their favorite one is unavailable. This customer-driven demand substitution affects the optimal order allocation decisions (Yücel *et al.*, 2009). Demand substitution is an essential parameter for product assortment optimization and inventory management (Kök and Fisher, 2007; Kök *et al.*, 2008; Pentico, 2008; Yücel *et al.*, 2009; Singh and Kapoor, 2013). For the customer-driven demand substitution behaviors, demand models are classified as multinomial logit, locational choice, and exogenous demand models (Kök *et al.*, 2008). The multinomial logit and locational choice models are utility-based models commonly used in economics marketing literature. Exogenous demand models directly specify the demand for each product and provide preferences of individuals when their favorite product is not available.

Vaccine availability, efficacy, and citizens' preferences are primary factors limiting the number of inoculations. Harapan *et al.* (2020) stated that the baseline effectiveness of a Covid-19 vaccine highly influenced its acceptance by the public. If the preferred vaccine is not available, citizens may make a substitution. However, the desire to substitute from high to low effective vaccines may be small. Borriello *et al.* (2021) studied the vaccine preferences and realized that immediacy, effectiveness, and side effects were the significant determinants of choice. They used an exogenous model to consider the aggregate behavior of citizens. Under the exogenous models, the deterministic proportion assumption denotes the cumulative substitution rates and is widely utilized in stockout-based substitution models (Netessine and Rudi, 2003).

Supplier reliability under uncertainty becomes an important issue because of late deliveries and quality problems (Smeltzer and Siferd, 1998). A supplier is perceived as reliable when deliveries are made according to contract and relevant information is provided timely and accurately (Selnes and Gønhaug, 2000). Uncertainty and risks impact both supply chain design and supply chain planning decisions. Recurrent or operational risks and disruptive risks (Tang, 2006; Chopra *et al.*, 2007; Tsai, 2016; Ivanov, 2017; Rezapour *et al.*, 2017) are typically involved in those considerations. Demand and lead-time uncertainty risks are frequently considered operational risks (Kleindorfer and Saad, 2005; Chopra *et al.*, 2007; Acar *et al.*, 2010; Georgiadis *et al.*, 2011; Hora and Klassen, 2013; Meisel and Bierwirth, 2014).

In this study, multi-objective optimization is used to optimize a collection of objectives simultaneously. One of the most common approaches to multi-objective optimization is the weighted sum method (Marler and Arora, 2004). AHP and the weighted-sum methods are integrated into the framework evaluation by Rădulescu and Rahoveanu (2011). Our study introduces a vaccine order allocation model with product substitution and a weighted-sum method to consider three objectives: total inefficient and postponed vaccinations and cost. AHP is used to determine the weights of the objectives. In this respect, our study is one of the first studies directly targeting the social objectives such as total inefficient and postponed vaccinations to reduce as separate entities in the primary objective function. Along with weights allocated to the objectives, the substitution decisions among the different vaccine types are integrated into the allocation decisions. The study also presents an illustrative example compiled for the Covid-19 pandemic, in which data are gathered from readily available public resources with unpredictable capacity information of the vaccine suppliers.

3. Problem definition and model formulation

The problem addressed in this study considers a supply chain with a single buyer (government) and multiple suppliers, each producing different types of vaccines with varying efficacy and storage conditions. The study formulates the problem as a multi-objective vaccine order allocation model. The objectives are set as purchasing costs, postponed vaccinations, and ineffectively vaccinated people. The government decides the number of vaccines to be ordered from every supplier according to citizens' preferences by assuming exogenous substitution ratios among different vaccines in the model. Supplier delivery capacity is uncertain and varies according to the supplier's reliability. The uncertainty in this study is tackled by the scenario analysis under optimistic (O), most likely (ML), and pessimistic (P) conditions. The storage capacity of vaccine centers varies depending on the types of vaccines.

In this study, the multi-period vaccine order allocation problem using an exogenous substitution matrix is formulated as a mixed-integer linear programming model. This model calculates the vaccines to be ordered from various suppliers while minimizing cost, postponing vaccinations, and ineffectively vaccinating people for optimistic, most likely, and pessimistic scenarios. If the vaccine is not available, it is assumed that the people may either accept an alternative vaccine or postpone the vaccination to a future period. Additionally, suppliers are considered to have different reliability levels. Spoil rate of each vaccine changes based on the type of vaccine and scenario.

Parameters, decision variables, objective function, and constraints of the model introduced here are given below:

Sets	
S	Scenarios set
T	Periods set
I	Vaccines set
Parameters	
p_i	Unit price of a vaccine *i*
h_i	Holding cost of vaccine *i* for one period
F_i	Freezer installation cost for vaccine *i*
e_i	Effectiveness of vaccine-type *i*
e_{max}	Maximum vaccine effectiveness ($\max_i e_i$)
spl_{it}^s	Spoil rate of vaccine-type *i* at period *t* under scenario *s*
O_{it}	Order quota offered by the supplier for the vaccine type *i* at time *t*
$O_{realized}{it}^s$	Delivery quantity by the supplier for the vaccine type *i* at time *t* under scenario *s*
v_i	Inventory capacity of the freezer for the vaccine type *i*
pr(s)	Probability of scenario s
u_i	Time between subsequent orders for vaccine-type *i*
VC	Vaccination capacity of the government for one period
θ_{ki}	Substitution ratio of vaccine-type *k* by the vaccine type *i*
D_{it}^s	Planned vaccination quantity of type *i* at period *t* under scenario *s*
Decision variables	
Q_{it}^s	Number of inoculated people with vaccine-type *i* at period *t* under scenario *s*
x_{it}	The number of vaccine-type *i* received at period *t*. The vaccine is ordered by considering the duration of lead time
$x_{over}{it}^s$	The excessive number of vaccine-type *i* ordered more than the realized order quota at period *t* under scenario *s*
xf_{it}^s	The number of fulfilled demands by the vaccine type *i* at period *t* under scenario *s*
xs_{kit}^s	The number of vaccine-type *k* substituted by vaccine type *i* at period *t* under scenario *s*
xb_{it}^s	The number of vaccinations of type *i* postponed at period *t* under scenario *s*
z_{it}	*1* if vaccine type *i* ordered at period *t*, *0* otherwise
y_i	The number of freezers purchased for vaccine-type *i*
I_{it}^s	Inventory level of vaccine-type *i* at period *t* under scenario *s*
Z_1	Expected value of total inefficient vaccination
Z_2	Expected value of total postponed vaccination
Z_3	Expected value of total cost

3.1 Objective functions

MIP model has three objectives to minimize the deviations from the inefficient and postponed vaccination targets and costs. The model provides a unique solution considering three scenarios (O, ML, P), each of which happens with a certain probability.

$$Z_1 = \sum_i \sum_t \sum_s pr(s)\left[e_{\max} D_{it}^s - e_i Q_{it}^s\right] \quad (1)$$

$$Z_2 = \sum_s \sum_i \sum_t pr(s) xb_{it}^s \quad (2)$$

$$Z_3 = \sum_i \sum_t \sum_s pr(s)\left[\left(x_{it} - x_{\text{over}_{it}^s}\right)p_i + I_{it}^s h_i\right] + \sum_i y_i F_i \quad (3)$$

The objective functions in Equations (1) and (2) present the expected values of total inefficient and postponed vaccinations. The number of inefficient vaccinations is calculated by the discrepancy between possible maximum effective vaccinations planned ($e_{\max} D_{it}^s$) and the effectively inoculated people with vaccine-type i. The objective function in Equation (3) shows the expected value of cost components as a summation of vaccines' purchasing and storage expenses and the investment cost of freezers. The purchasing cost is the price times the number of vaccines received (x_{it}). The government should immunize as many people as possible without any postponements with the least possible cost by providing an effective vaccine plan.

3.2 Constraints

The model for the constraints is then formulated considering vaccine substitutions and scenarios as follows:

$$Q_{it}^s = \left(1 - spl_i^s\right)\left(x_{it} - x_{\text{over}_{it}^s}\right) + I_{i(t-1)}^s - I_{it}^s \quad \forall i,\ t,\ s \quad (4)$$

$$I_{it}^s = 0 \qquad t = 0,\ \forall i,\ s \quad (5)$$

Constraint set (4) calculates the number of inoculated people based on the number of vaccines received, spoiled, and stored from the previous period and unused vaccines carried to the next period. Constraint (5) guarantees no vaccine to keep at the beginning.

$$x_{it} \le O_{it} \qquad \forall\ i,\ t \quad (6)$$

$$x_{it} - x_{\text{over}_{it}^s} \le z_{it} O_{\text{realized}_{it}^s} \qquad \forall\ i,\ t,\ s \quad (7)$$

$$x_{it} - x_{\text{over}_{it}^s} \ge 0 \qquad \forall i,\ t,\ s \quad (8)$$

Equations (6)–(8) represent the order quotation constraints. Actual delivery quantities oscillate in scenarios based on supplier reliability. Despite the agreed order quota, suppliers may not deliver all orders but only a certain proportion of this quantity. Constraint (6) shows that government cannot order and receive more than the order quota. Constraint (7) guarantees that the difference between the planned order quantity and $x_{\text{over}_{it}^s}$ should be less than or equal to realized delivery quantity. This constraint set is required since the planned order quantity is fixed for all scenarios; however, the delivery quantity of suppliers changes in every scenario. Constraint (8) ensures that the amount of vaccine received should be higher than the excessive quantity of vaccine ordered.

$$xf_{it}^{s} + \sum_{k} xs_{ikt}^{s} = D_{it}^{s} - xb_{it}^{s} + xb_{i(t-1)}^{s} \quad \forall i,\ t \tag{9}$$

$$xf_{it}^{s} + \sum_{k \neq i} xs_{kit}^{s} = Q_{it}^{s} \quad \forall i,\ t \tag{10}$$

$$xs_{ikt}^{s} \leq \left(D_{it}^{s} - xf_{it}^{s} + xb_{i(t-1)}^{s}\right)\theta_{ik} \quad \forall i,\ t,\ k \neq i \tag{11}$$

$$xb_{it}^{s} = 0 \qquad t = 0,\ \forall i, s \tag{12}$$

Equations (9)–(12) provide information about the relationship among vaccine substitutions and the number of vaccinations planned and postponed. Equation (9) shows the balance between planned vaccinations with postponement consideration and the summation of directly fulfilled and substituted vaccine supplies. Equation (10) indicates that the number of people vaccinated with a specific type of vaccine is the sum of the people who request this type of vaccine firsthand and those who get a substitution for other vaccines. Equation (11) expresses that substitution quantity between two vaccines is limited to a specific ratio of the total planned vaccination, including postponed portions from previous periods after subtracting direct fulfillments from this total. Constraint (12) shows no postponed vaccination at the beginning of the planning horizon.

$$\sum_{i} Q_{it}^{s} \leq VC \quad \forall t, s \tag{13}$$

$$\sum_{t}^{t+u_i} z_{it} \leq 1 \quad \forall i,\ t \tag{14}$$

$$0 \leq v_i y_i - I_{it}^{s} \quad \forall i,\ s,\ t \tag{15}$$

$$x_{it},\quad xf_{it}^{s},\ xs_{kit}^{s},\quad xb_{it}^{s},\quad Q_{it}^{s},\ I_{it}^{s},\quad y_i \in Z^{+} \qquad \forall\ i, t,\ s \tag{16}$$

$$z_{it} \in \{0, 1\} \quad \forall\ i, t \tag{17}$$

As given in equation (13), one of the significant limitations is the government vaccination capacity in each period. Constraint (14) assures that the government can order once in every ordering period. The maximum number of vaccines carried in the freezer should be less than the freezer capacity. Equation (15) guarantees that government should purchase enough freezer capacity to store vaccines. Constraint (16) shows nonnegative discrete variables, whereas constraint (17) states binary variables.

4. Solution methodologies

The following subsections present the multi-objective order allocation solution approach and the AHP structure to determine the objectives' weights.

4.1 Multi-objective weighted sum function

The weighted sum method to solve the multi-objective optimization model is proposed in this study to minimize the weighted sum of scalarized objective functions as given in Equation (18).

$$\text{Min} \quad Z = \sum_{j=1}^{J} \omega_j N(Z_j) \tag{18}$$

where,

ω_j Weight of the objective function j such that $\sum_j \omega_j = 1$

$N(Z_j)$ Normalized value of the objective function j such that $0 \leq N(Z_j) \leq 1$

Equation (18) shows the combined objective function of the model as a weighted and normalized sum of three objectives. The calculation of weights for the objectives is explained in the following subsection.

This study adopts the upper-lower bound normalization approach producing a value between zero and one (Marler and Arora, 2005). The normalization function is defined in Equation (19) as follows:

$$N(Z_j) = \left(Z_j - Z_j^{\min}\right) \Big/ \left(Z_j^{\max} - Z_j^{\min}\right) \quad j = 1,2,3 \tag{19}$$

where,

Z_j Actual value of the objective function j.

$Z_j^{\min}$ Lower bound of the objective function j.

$Z_j^{\max}$ Upper bound of the objective function j.

The performance of the normalization approach depends on the accuracy and the method to determine lower and upper bounds; however, this approach is still relatively robust compared to the other approaches in the literature (Marler and Arora, 2005).

The lower bounds are determined as the minimum value of the objective functions by solving the model given in Section 3 for minimizing each objective function separately. The upper bounds are set as $Z_j^{\max} = \max_k Z_j(f_k^*)$, where f_k^* is the solution point that minimizes the kth objective function. The approach to determining lower and upper bounds used in this study has also been found more conducive to multi-objective optimization by (Marler and Arora, 2005).

4.2 AHP for the weight assignment

In the MIP model above, the weights of the objectives are identified by AHP. AHP is a multicriteria decision-making method that breaks down the decision-making into layers of a hierarchy in which relationships among objectives, criteria and decision alternatives are defined separately (Saaty, 2004; Wang *et al.*, 2012).

The objectives selected for the MIP model are to minimize postponed vaccination, inefficient vaccination, and purchasing cost; each has a different impact on the solution of the MIP model. The late deliveries of suppliers result in the postponement of vaccinations and cause a delay in providing herd immunity in society. Thus, the delay destroys social affairs while extending COVID-19 related precautions and societal restrictions. Inefficient vaccination is due to the type of vaccine selected. Each vaccine type has a specific efficacy, and if the government buys a vaccine type with less efficacy, this strategy results in lower immunization rates in society.

To evaluate the objectives, social, health-related, and economic factors are considered as primary criteria. Each criterion also breaks down into three sub-criteria, as shown in Table 1, where each of them directly affects the primary objective at different levels. Weights (w_1, w_2, and w_3) for these objectives are obtained from AHP. Table 1 presents the criteria for determining the weights of the objectives for the vaccine order allocation model.

Clinical attack rates (CARs) are key epidemiological factors used as clinical outcomes to predict the impacts of health costs on government budgets and consumption (Keogh-Brown *et al.*, 2020). The other unavoidable factors observed in the healthcare sector are morale falloffs (MFOs) and healthcare personnel shortages (HPSs). Many factors can be used to estimate the direct and indirect effects of a pandemic on the economy, such as income losses (ILs) due to business closures, budget constraints (BCs) due to high costs, and unemployment surges (USs) due to job losses in many sectors. Preventive measures to mitigate or suppress the effects of pandemics on public health result in school closures (SCs), travel restrictions (TRs), and social distancing (SD). The factors given in Table 1 represent the criteria for evaluating a vaccination plan by the governments. In Figure 1, the AHP model hierarchy reveals how to determine the weights of the objectives in the mathematical model above by considering social, economic, and health-related criteria.

Table 1 AHP criteria and sub-criteria to determine the weights of the objectives

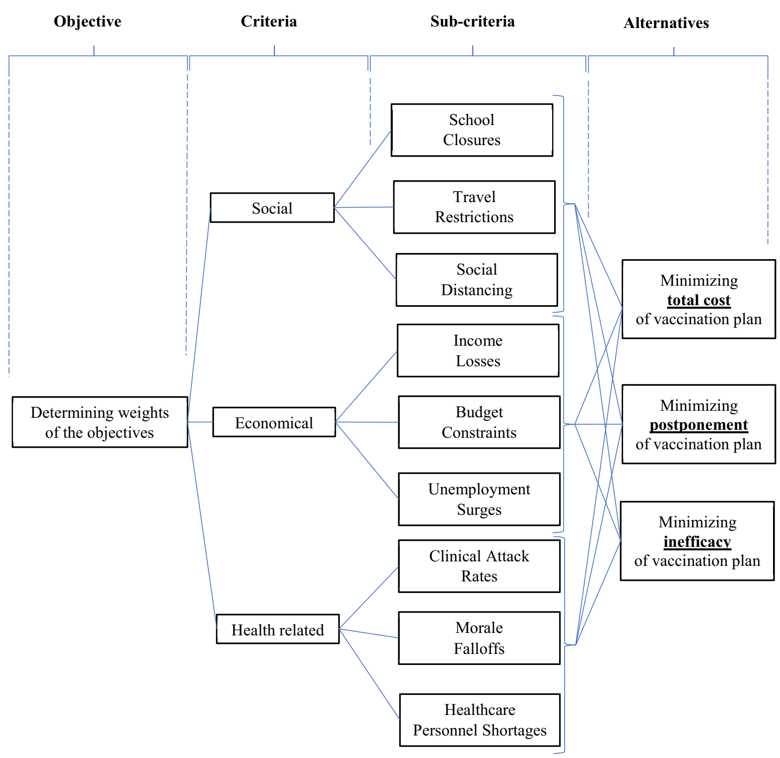
Criteria	Sub-criteria
Social	School Closures (SCs)
	Travel Restrictions (TRs)
	Social Distancing (SD)
Economical	Income Losses (ILs)
	Budget Constraints (BCs)
	Unemployment Surges (USs)
Health-related	Clinical Attack Rates (CARs)
	Morale Falloffs (MFOs)
	Healthcare Personnel Shortages (HPSs)

Essential steps in the decision-making process of AHP are constructing the hierarchy, pairwise comparison among criteria and pairwise comparison of alternatives for each measure, consistency checking, and determining the weights. The government needs to determine specialists from different sectors to evaluate the options and metrics. These specialists provide the expert opinions for pairwise comparisons represented in a judgment matrix. Pairwise comparisons produce the weight of each criterion and alternative based on the eigenvector method. These weights are validated only if the degree of consistency is satisfactory. Otherwise, comparison matrices need to be revised (Saaty, 2004; Wang *et al.*, 2012).

5. Illustrative example and experimental study

In this section, a numerical example illustrates the proposed model for a hypothetical Covid-19 supply chain. We also conduct experimental studies on uncertain parameters to show the effect of the variability on solutions. The MIP using the exogenous substitution probabilities model is developed and solved for alternative scenarios. The following subsections present an illustrative example and experimental studies.

Figure 1 AHP hierarchy to determine the weights of the objectives used in the mathematical model



5.1 Illustrative example and results

This section presents a hypothetical example to illustrate the proposed model. The vaccine data but the substitution ratios in the example problem are gathered from the readily available public information for the Covid-19 vaccine. The example illustrates a supply chain structure with a single buyer (government) and three suppliers producing one type of vaccine. The exemplary supply process is presented in the following figure.

For the COVID-19 pandemic, several vaccine candidates are being developed, and numerous vaccines are currently in clinical trial phases. Different vaccine design approaches exist (World Health Organization, 2021b). We consider only mRNA, inactivated, and viral vector vaccines among many types, as seen in Figure 2. The mRNA vaccine should be stored in an ultra-low temperature freezer and transported frozen via a cold supply chain. The government needs to invest extra to keep a vaccine ultra-cold, between −60 °C and −80 °C. Inactivated and viral vector vaccines are stable in a regular freezer. Current conditions in most health centers do not require any additional investment for storing vaccines except mRNA vaccines. A freezer to keep the mRNA vaccine is approximately $25,000, with a capacity of 70,000 units.

This illustrative example assumes three supplier variants with different reliability levels. Supplier reliability is defined as the discrepancy between planned and realized delivery. The highly reliable supplier should deliver 95 to 100% of the order quota provided to the government. The supplier with medium reliability may provide 70 to 85% of the order quota requested by the government. The supplier with low reliability may deliver only 45 to 60% of the order quota. Table 2 presents the distributions of percentage realized capacities of suppliers for optimistic, most likely, and pessimistic scenarios. As seen in Table 2, the supplier's reliability is given as the percentage of actual delivery. For instance, the highly reliable supplier delivers according to U[95%, 100%] in the optimistic scenario, which shows that the delivery realization of this supplier is somewhere between 95 and 100% of the order quota given to the government.

The weekly order quotas for high, medium, and low reliable suppliers are assumed to be 1, 3, and 5M, respectively. The government prepares procurement plans according to the order quotas given by the suppliers. However, realized delivery quantities would be different from the order quotas declared because of the variability in the supply process. On the other hand, all suppliers are assumed to deliver the order quantities within the same week of the order received from the government. Thus, the lead time of the suppliers for the example problem is assumed to be negligible. The weekly inoculation capacity of the government is considered 4M, and this capacity is allocated to three suppliers according to the preference of the citizens. The weekly planned inoculation quantities for mRNA, inactivated, and viral vectoral vaccines are 1, 2, and 1M, respectively. We assume that if a vaccine is unavailable because of not provided or stocked out, it is substituted with an alternative vaccine or postponed to a later period. Product substitution decisions affect the order allocation and inventory held each week. Thus, our model includes specific substitution ratios among vaccine types, as shown in Figure 2. The substitution ratios among vaccine types are assumed to be exogenous. For instance, if there is no availability for mRNA vaccines, 40% of the citizens registered

Figure 2 Vaccine supply process of the illustrative example

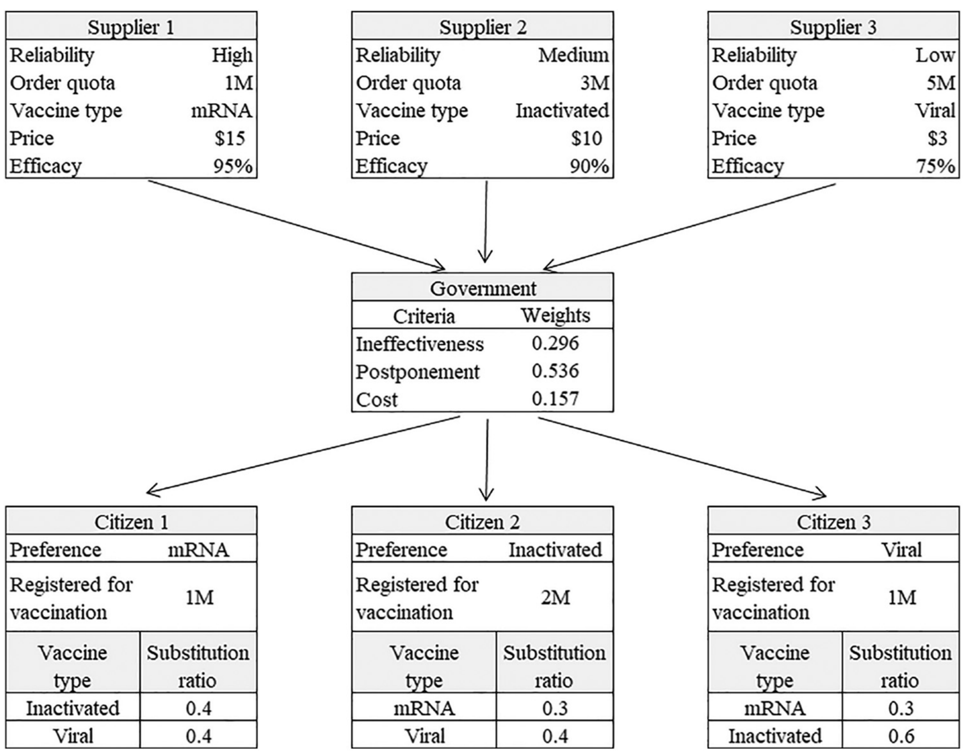


Table 2 Reliability distributions for the on-time delivery performance of suppliers under each scenario

Scenario	Supplier 1 (high reliability)	Supplier 2 (medium reliability)	Supplier 3 (low reliability)
O	U[95%, 100%]	U[70%, 85%]	U[45%, 60%]
ML	U[90%, 100%]	U[60%, 80%]	U[30%, 50%]
P	U[85%, 95%]	U[50%, 75%]	U[15%, 40%]

for mRNA place their preferences for inactivated vaccines, whereas another 40% prefer viral ones. The remaining 20% chooses to wait until mRNA is available.

Domestic and cross-border freights are not fully operational under the pandemic. Thus, many vaccine suppliers face severe supply shortages, where the health supply chain is adversely affected by the variability in the actualization of supply capacities. This study generates optimistic (O), most likely (ML), and pessimistic (P) scenarios for the variability in the actualization of supply capacities. The probability of each scenario is also given in Table 3.

The proposed model also considers spoilage of vaccines due to misusage or improper storage conditions. Therefore, we assume that a proportion of vaccines are spoiled based on the vaccine type and scenario, as shown in Table 4.

The mathematical model is solved for each objective function, and the other objectives are also calculated in each solution. For each objective function, minimum and maximum values are calculated by solving the MIP model only for this objective under different scenarios and assigned as upper and lower bounds in normalization equations given in equation (5). The upper and lower bounds of each objective are shown in Table 5.

The objective function in equation (1) is presented with normalized values as follows:

Table 3 Scenario probabilities

Scenario	Probability
Optimistic (O)	0.25
Most likely (ML)	0.5
Pessimistic (P)	0.25

Table 4 Vaccine spoil rates

Scenario	Vaccine type mRNA	Inactivated	Viral vectoral
O	0.05	0.01	0.01
ML	0.07	0.02	0.02
P	0.10	0.03	0.03

Table 5 $Z_{\min}$ and $Z_{\max}$ values for each objective function

	Z_1	Z_2	Z_3
Min	6,914	1,080	0
Max	68,400	84,000	230,190

$$\text{Min } Z = \omega_1 \frac{(Z_1 - 6{,}914)}{(68{,}400 - 6{,}914)} + \omega_2 \frac{(Z_2 - 1{,}080)}{(84{,}000 - 1{,}080)} + \omega_3 \frac{Z_3}{23{,}0190} \quad (20)$$

The summary of AHP results is presented in Figure 3 and Table 6. The government wants to determine the order quantity for each vaccine type to increase herd immunity in the society rapidly, so minimizing ineffective vaccination and postponed vaccinations are more crucial than reducing costs. The weights of the objectives are determined as 0.296, 0.567, and 0.137 for $N(Z_1)$, $N(Z_2)$, and, respectively. These weights are used in the solution of the model to determine order quantities. The proposed MIP models with 162 decision variables were implemented in General Algebraic Modeling (GAMs) 23.5 and solved with ILOG CPLEX on a computer with Intel(R) Core (TM) i75 CPU, a 1.80 GHz processor, and 16 GB R3 memory using Windows 10 (64 bit). Solutions were obtained within 50 iterations and 5 min of elapsed time. The model results are given in Table 7, which shows objective function values and percentage deviation from lower bounds.

The lower values of percentage deviation indicate the successful actualization of an objective. Tables 6 and 10 show that 174 people have ineffective vaccination, 4,922 vaccinations are postponed, and the total purchasing cost is 205,818 USD for a six-week plan.

For each vaccine type, vaccination plans may be prepared from the results. For the sake of simplicity here, a vaccination plan for only mRNA vaccines is given in Tables 8–10, under the delivery capacity of optimistic, most likely, and pessimistic scenarios. The second and third columns in the tables are planned order quantities and realized order quantities, which are essential decision variables for the model to show outcomes of order allocation. Planned order quantities are equal; however, realized order quantities vary depending on delivery realizations and substitution quantities.

The fourth column in Tables 8–10 shows the number of people vaccinated with their requested type of vaccine, mRNA. The fifth and sixth columns show the number of substituted vaccines by the inactivated and viral vectoral ones due to the unavailability of mRNA. Therefore, the total number of people initially preferring mRNA vaccines is the sum of these three columns. If the number of vaccines is not enough to meet the planned quantities by the government, they are postponed to the next period. The number of postponed vaccinations is cumulative values depending on the actualization of supplier capacities. Therefore, there is a significant difference between optimistic and pessimistic scenarios. The last three columns in the tables show the total number of mRNA vaccines administered and substituted by inactivated and viral vectors ones.

Table 11 shows the percentage order allocations of suppliers and the percentage of postponed vaccinations of each type. The table shows that 15.4, 40.2, and 44.5% of planned vaccination are met with mRNA, inactivated, and viral vectoral vaccines, respectively. When a specific vaccine is unavailable, it is either substituted by another vaccine or postponed for the next period. 60.8, 22.3, and 16.9% of postponed vaccinations are viral vectoral, inactivated, and mRNA vaccines, respectively.

Figure 3 Results of criteria weights according to expertise pairwise comparison

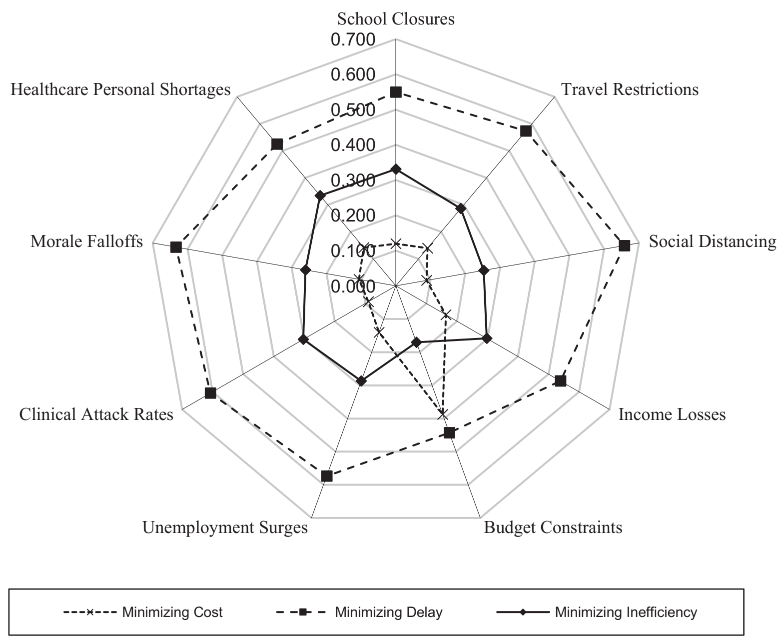


Table 6 AHP weights calculations for the MIP model objectives

Objectives	SCs (0.21)	TRs (0.05)	SD (0.04)	ILs (0.09)	BCs (0.06)	USs (0.13)	CARs (0.21)	MFOs (0.08)	HPSs (0.13)	Weights of the objectives
Minimizing Inefficacy (Z_1)	0.33	0.29	0.25	0.30	0.17	0.29	0.30	0.26	0.33	0.296
Minimizing Postponement (Z_2)	0.55	0.57	0.66	0.54	0.44	0.57	0.61	0.63	0.52	0.567
Minimizing cost (Z_3)	0.12	0.14	0.09	0.16	0.39	0.14	0.09	0.11	0.14	0.137

Table 7 MIP model results for each objective

Objective function	Weights	Percentage deviation	Value
Z	–	–	0.164
Z_1	0.296	0.048	10,174
Z_2	0.567	0.046	4,922
Z_3	0.137	0.894	205,818

Table 12 shows the results related to overall substitution and postponed vaccinations in all scenarios. As seen in the table, postponed vaccination quantities significantly increase from optimistic to pessimistic scenarios, which shows that capacity realization has a tremendous impact on the overall performance of vaccine planning. Only 1.4% of the planned order vaccines are postponed in the optimistic scenario, while this quantity increases to 43.1% under the pessimistic scenario.

Table 13 shows the expected number of substitutions among vaccine types considering all scenarios. The results reveal that mRNA is substituted commonly by the other vaccine types. On the other hand, the number of substitutions from viral vectoral to the others is relatively low. The purchasing cost can explain these trends since the viral vectoral is the least cost vaccine, whereas the mRNA is the highest cost.

5.2 Experimental study

The experimental study is conducted to analyze the sensitivity of the proposed model to some of its essential parameters, such as the time between recurring orders and the substitution ratios among vaccine types.

5.2.1 The impact of time between recurring orders

Initially, it is assumed that the government may order any vaccine type every week. However, suppliers may have limitations in processing frequent recurring orders in real life and thus need a specific time between two consecutive order placements. This section presents a numerical analysis to observe the effect of the time between recurring orders on the objective function. For two to three weeks' time intervals between recurring orders, the results are presented in Figure 4. When the time between recurring orders increases, the total objective function value as a weighted average of deviations from all objectives, Z-values, worsens as deviations from minimum values of inefficacy and postponed quantities increase. However, as seen in Figure 4, variations from minimum cost value decrease as the number of weeks between recurring orders increases.

Figures 5 and 6 depict the change in the ratio of postponed to planned quantities and the proportion of substituted to planned

Table 8 Vaccination plan for mRNA in the optimistic scenario

			Number of people requesting mRNA vaccinated with						Substituted for	
Week t	Planned order quantity $x_{1,t}$	Realized order quantity $O_{\text{realized}^1_{1,t}}$	mRNA ($i = 1$) $xf^1_{1,t}$	Inactivated ($i = 2$) $xs^1_{k=2,1,t}$	Viral vector ($i = 3$) $xs^1_{k=3,1,t}$	Number of postponed vaccinations $xb^1_{1,t}$	Inventory level $I^1_{1,t}$	Total number of people vaccinated with mRNA $Q^1_{1,t}$	Inactivated $xs^1_{1,k=2,t}$	Viral vector $xs^1_{1,k=3,t}$
1	960	960	795	82	82	41	0	912	117	0
2	890	890	755	114	114	57	0	846	90	0
3	1,000	940	893	66	66	33	0	893	0	0
4	970	970	897	54	54	27	0	922	25	0
5	800	594	354	269	269	135	210	354	0	0
6	1,000	940	1,103	13	13	6	0	1,103	0	0

Table 9 Vaccination plan for mRNA in most-likely scenario

			Number of people requesting mRNA vaccinated with						Substituted for	
Week t	Planned order quantity $x_{1,t}$	Realized order quantity $O_{\text{realized}^1_{2,t}}$	mRNA ($i = 1$) $xf^2_{1,t}$	Inactivated ($i = 2$) $xs^2_{k=2,1,t}$	Viral vector ($i = 3$) $xs^2_{k=3,1,t}$	Number of postponed vaccinations $xb^2_{1,t}$	Inventory level $I^2_{1,t}$	Total number of people vaccinated with mRNA $Q^2_{1,t}$	Inactivated $xs^2_{1,k=2,t}$	Viral vector $xs^2_{1,k=3,t}$
1	960	589	560	176	176	29	0	560	0	0
2	890	852	721	147	147	52	0	809	89	0
3	1,000	783	659	166	166	75	0	744	85	0
4	970	595	405	271	271	208	0	565	160	0
5	800	380	0	454	454	242	0	361	361	0
6	1,000	149	0	491	491	248	0	141	141	0

Table 10 Vaccination plan for mRNA in the pessimistic scenario

			Number of people requesting mRNA vaccinated with						Substituted for	
Week t	Planned order quantity $x_{1,t}$	Realized order quantity $O_{\text{realized}^3_{1,t}}$	mRNA ($i = 1$) $xf^3_{1,t}$	Inactivated ($i = 2$) $xs^3_{k=2,1,t}$	Viral vector ($i = 3$) $xs^3_{k=3,1,t}$	Number of postponed vaccinations $xb^3_{1,t}$	Inventory level $I^3_{1,t}$	Total number of people vaccinated with mRNA $Q^3_{1,t}$	Inactivated $xs^3_{1,k=2,t}$	Viral vector $xs^3_{1,k=3,t}$
1	960	900	555	178	0	87	0	855	0	300
2	890	824	0	507	0	132	0	783	512	271
3	1,000	834	0	704	0	282	0	792	401	391
4	970	786	0	822	822	203	0	747	747	0
5	800	758	349	425	379	722	0	720	371	0
6	1,000	720	0	503	0	460	0	684	0	684

Table 11 Vaccine order allocation and postponed vaccination percentages among vaccine types

Vaccine type	Percentage of order allocation	Percentage of postponed vaccinations
mRNA	15.4%	16.9%
Inactivated	40.2%	22.3%
Viral vectoral	44.5%	60.8%

vaccinations while increasing the time between recurring orders in vaccination planning.

As seen in Figure 6, substitution quantities in optimistic and most likely scenarios, but the pessimistic scenario, increase as the time between recurring orders increases. The contradicted behavior of pessimistic scenarios can be explained by the lower availability of capacity substituting for another vaccine type.

Table 12 The postponed and substituted vaccinations for each scenario

Scenario	# of postponed vaccination	Ratio of postponed to planned vaccination	# of substituted vaccination	Ratio of substituted to planned vaccination
O	530	1.4%	1,736	4.7%
ML	1,688	4.6%	5,361	14.6%
P	15,779	43.1%	13,936	38.1%

Table 13 Substitution quantities among vaccine types

	mRNA	Inactivated	Viral vectoral
mRNA	0	984	411
Inactivated	1,787	0	658
Viral vectoral	1,302	1,457	0

Figure 4 The effect of time between orders on objectives of the model

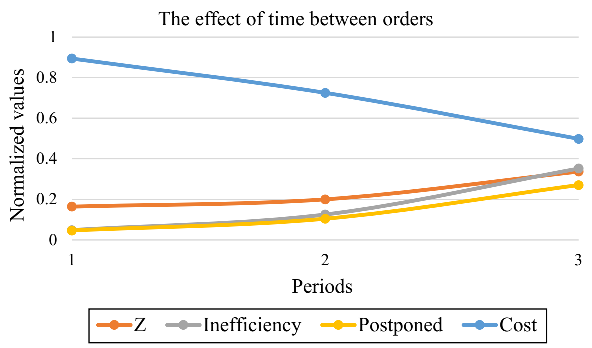


Figure 5 The ratio of postponed to the planned vaccination

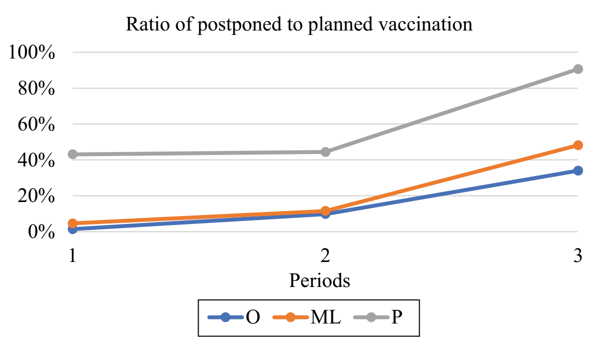
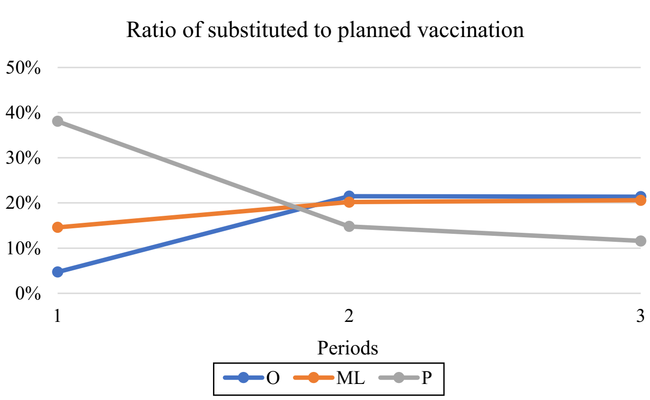


Figure 6 The ratio of substituted to the planned vaccination



5.2.2 The impact of changing substitution ratios

The substitution ratios indicating the rate of substitutions among vaccines are set as high, moderate, and no substitution. Table 14 shows the substitution matrix for high substitution ratios, which assumes that people prefer to switch from one vaccine to another instead of postponing their vaccinations. Thus, substitution ratios are zero from any vaccine to the postponement. Moderate substitution ratios are gathered from Figure 2, and their analysis is discussed in Section 4.1. No substitution scenario assumes that all planned vaccinations not fulfilled directly are postponed to further periods.

The impact of substitution ratios on objective function values is revealed in Figure 7. It is observed that objective function values (Z, Z_1, and Z_3) slightly increase as changing from high substitution to no substitution except for the objective of minimizing inefficacy (Z_1).

The impact of substitution ratios on the ratio of postponed to planned vaccination quantities and substitution to planned vaccination quantities are given in Figures 8 and 9. A vaccination plan has no postponed vaccination when the substitution level is assumed to be high in which substitution rates are significantly large among vaccine types. Postponed vaccination quantities in optimistic and most likely scenarios increase as the substitution levels change from high to no substitution. However, changing substitution levels does not affect amounts postponed in the pessimistic scenario since realized delivery quantities are too low to substitute another vaccine type.

6. Conclusion and future research directions

This study investigates a multi-objective vaccine allocation problem by considering vaccine substitution and supplier reliability under optimum, most likely, and pessimistic scenarios. The impact of Covid 19 is discussed, relying on numerous factors such as health care, social, and economic to minimize its effect on a country. Experimental analysis is conducted to evaluate the impact of time between orders, substitution ratios, and supplier reliability on the government vaccine allocation plan.

The hypothetical data analysis reveals that the MIP model may provide essential insights to the decision-makers for the vaccine allocation problem regarding the substitution among various vaccines, duration between consecutive orders, and supplier reliability. The viral vectoral vaccine has the lowest

Table 14 Substitution rates for the high substitution scenario

θ_{ki}	mRNA	Inactivated	Viral vector	Postponed
mRNA	–	0.50	0.50	0
Inactivated	0.45	–	0.55	0
Viral vectoral	0.35	0.65	–	0

Figure 7 The effect of substitution ratio levels on objectives

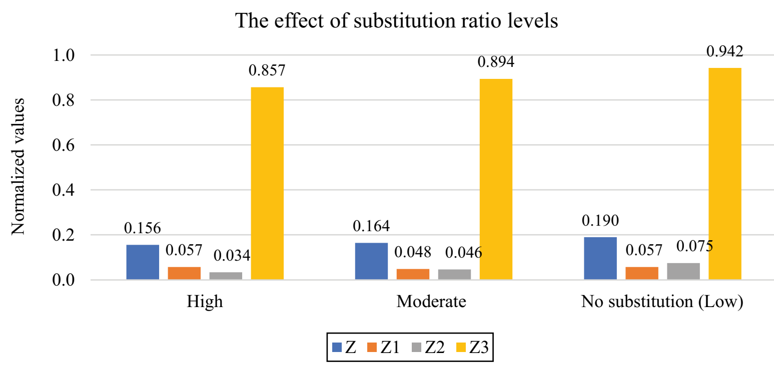


Figure 8 The effect of substitution ratio levels on the ratio of postponed to the planned vaccination

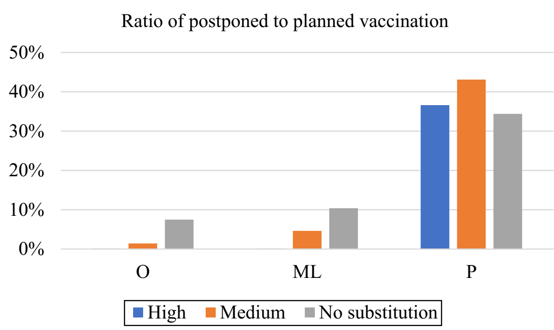
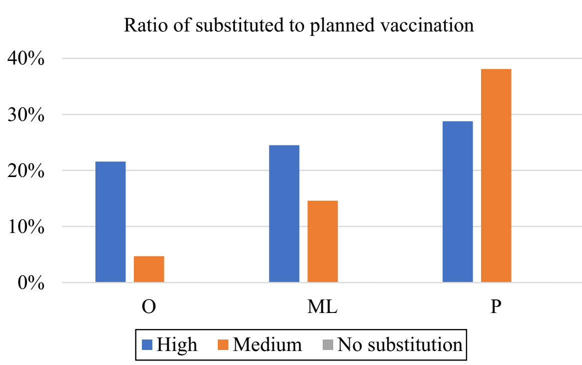


Figure 9 The effect of substitution ratio levels on the ratio of substituted to the planned vaccination



substitution ratio in the sample problem, while mRNA is the most substituted vaccine in the base scenario. The model shows that inexpensive vaccines will replace expensive ones if possible. Another significant insight is about the time between recurring orders. Although the same amount of vaccine is available in scenarios with an increasing duration between recurring orders, the sum of the weighted average of deviations from all objectives, *Z*-value, gets worse, and deviations from minimum values of inefficacy and postponed quantities increase.

On the other hand, total cost descends since the time between recurring orders affects the available supplier capacity. Besides, substitution level has a significant impact on postponed quantities. When the substitution ratios are significantly large between vaccine types, the postponed vaccinations go down to zero. Postponed vaccination quantities in optimistic and most likely scenarios increase as the substitution levels change from high to no substitution. However, changing substitution levels does not affect amounts postponed in the pessimistic scenario since capacities are too low to substitute another vaccine type.

The MIP model developed in this study is an invaluable tool supporting governments in allocating the best vaccine by considering the number of postponed vaccinations, vaccine efficacy, and purchasing cost. The results of the hypothetical study show that the government should motivate people to get vaccinated as early as possible without considering the type of vaccine. The model indicates that inexpensive vaccines might be preferred to expensive ones as long as a substitution exists.

The vaccine markets under pandemic conditions are unstable since there are many uncertainties about suppliers, vaccines, and conflicts among governments. Therefore, the government should prefer to make agreements with high reliable suppliers. Besides, the government should push suppliers to have minimum time between orders. While deciding the vaccines and their order sizes, governments should not consider the price and effectiveness of vaccines in the first place. Instead, a reliable supplier should be targeted to start the vaccination process at the earliest time.

An illustrative data set with a limited number of vaccines and their exogenous substitution rates are studied to test the proposed model. In further studies, substitution between vaccines might be calculated with logistic regression based on the real-time data for more vaccines. Moreover, it is assumed that the number of vaccines will be allocated to various groups such as health employees and older adults. The MIP model may be modified to consider this group allocation problem. Substitution rates may also be calculated based on these groups. Finally, several modifications and extensions to the mathematical model developed in this paper are possible.

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Journal of Humanitarian Logistics and Supply Chain Management
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