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Multi-period vaccine allocation model in a pandemic: A case study of COVID-19 in Australia

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ABSTRACT

While the swift development and production of a COVID-19 vaccine has been a remarkable success, it is equally crucial to ensure that the vaccine is allocated and distributed in a timely and efficient manner. Prior research on pandemic supply chain has not fully incorporated the underlying factors and constraints in designing a vaccine allocation model. This study proposes an innovative vaccine allocation model to contain the spread of infectious diseases incorporating key contributing factors to the risk of uninoculated people including susceptibility rate and exposure risk. Analyses of the data collected from the state of Victoria in Australia show that a vaccine allocation model can deliver a superior performance in minimizing the risk of unvaccinated people when a multi-period approach is employed and augmenting operational mechanisms including transshipment between medical centers, capacity sharing, and mobile units being integrated into the vaccine allocation model.

1. Introduction

An epidemic is defined as a widespread occurrence of an infectious disease within a population or a country, while a pandemic is an epidemic that spreads beyond a population and a country's borders. In a pandemic the countries' health systems become overloaded. Limited production, transport, and storage capacity of vaccines increase the complexity of the vaccine supply chain which may result in ineffective delivery of vaccines to the right place at the right time (Fineberg, 2014). As of August 2021, worldwide 200 million COVID-19 cases and 4.3 million deaths have been reported (WHO, 2021a). In addition to such as a dramatic loss of human lives, the pandemic has caused much economic devastation and social disruption as well (Ali and Alharbi, 2020; Lima et al., 2020; Ozili and Arun, 2020; Carlsson-Szlezak et al., 2020). According to the International Monetary Fund (IMF, 2020), the COVID-19 pandemic is the worst economic downturn since the Great Depression.

The World Health Organization (WHO, 2021c) defines vaccination as a simple, safe, and effective way to protect people against harmful disease before they come into contact with them. However, the world is now suffering from a shortfall of vaccine production capacity and effective strategies for allocating and distributing vaccines. At the time of writing this article, less than 10 percent of the world's population have been fully vaccinated against COVID-19 (WHO, 2021a). With limited capacity of vaccine production there will be a long way to go to inoculate the remaining 7.1 billion people. The above discussion emphasizes the vital role that supply chains will play to mitigate the devastating effects of such pandemics.

Studies have been conducted to design an effective and efficient vaccine allocation and distribution network (Buccieri and Gaetz, 2013; Abbasi et al., 2020; Chen et al., 2020; Goldstein et al., 2012; Mamani et al., 2013; Araz et al., 2012; Ramirez-Nafarrate et al.,

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2015; Emu et al., 2021; Enayati and Özaltın, 2020). In most studies, the underlying factors in allocation and distribution network are considered individually. For example, a vital decision in vaccine allocation is prioritization of who is to be inoculated. Past studies use aspects of susceptibility to infectious diseases such as age (Chen et al., 2020; Foy et al., 2021) and medical history (Rao and Brandeau, 2021; Govindan et al., 2020) to prioritize individuals to receive a vaccine. As well as susceptibility, it is also important to note that geographic characteristics play an important role in any vaccine allocation decision (Yarmand et al., 2014). For example, areas with high population density have high levels of exposure to infectious diseases. Hence, due to the important role of both susceptibility rate and exposure risk, they should be simultaneously integrated in any vaccine allocation modeling.

A significant amount of studies on vaccine allocation is based on a single-period model (Abbasi et al., 2020; Schulte and Pibernik, 2016; Rao and Brandeau, 2021; Ekici et al., 2014). In a single-period allocation model, at the end of each period the excess vaccines would be returned to the distribution centers (DCs) if there is no unmet demand in medical centers (MCs) or transshipment capacity between MCs is already full. Furthermore, in a single-period allocation model the optimization decisions are based on each individual period ignoring the demand and resource capacities in future periods. This would result in sub-optimal solutions. In multi-period allocation model there is an opportunity to use the oversupplied vaccine to meet the demand of other MCs and achieve a more effective resource utilization rate than simply return them to the DCs. As highlighted recently by Choi (2021), examining risk in a multiple-period setting is more realistic and at the same time help researchers deal better with the dynamics of the COVID-19 pandemic. This would help the model to further reduce any residual risk of the unvaccinated population and significantly decrease the actual administrative horizon.

Another area which needs further research is the replenishment policy used in distribution centers as it can improve the vaccine administration process (Azadi et al., 2020). Abbasi et al. (2020) used a base-stock level policy in which a fixed level of vaccine supply became available in each period. Based on this policy, the returned vaccine units to DC are disregarded in each period, whereas we propose an allocation model in which the returned vaccines can be considered in future allocation decisions. In the single-period vaccine allocation, particularly when supply would be greater than total demand, it is quite possible to have significant amount of unmet demand in a number of medical centers while other MCs have excess vaccine supplies. Such a situation becomes more prevalent at the later stages of vaccine administration in which the likelihood of having MCs with zero or high demand would increase. This scenario leads to inefficiencies in the vaccine allocation model. To deal with such inefficiencies, cooperation and capacity sharing mechanism should be considered in a vaccine allocation model. Through such mechanisms under-utilized MCs would be able to offer their capacities to the MCs experiencing high demand. The mechanism provides the opportunity of redistributing the demand among eligible adjacent medical centers, which ultimately improves the allocation model' overall efficiency.

The spread of infectious deceases is dynamic and nonlinear in nature, because the infection rate is simply a product of the number of infected and uninfected people in a region. Consequently, the demand for vaccines in each period changes rapidly and in such circumstances, health authorities aim to employ all possible means and strategies to enhance the efficiency of vaccination operations. Research shows that mobile vaccination facilities can effectively cover larger regions compared to stationary vaccination sites (Halper and Raghavan, 2011). The role of mobile vaccination units become more prominent in remote regions, dense urban areas, and regions with highly dispersed populations (Halper and Raghavan, 2011; Muckstadt et al., 2021). While the majority of research on vaccine distribution uses stationary vaccine distribution units, we argue that mobile units should be included in a vaccine allocation model to diminish bottlenecks caused by the capacity constraints.

In this paper, the lack of a holistic approach to the vaccine supply chain motivates us to propose a more comprehensive vaccine allocation model incorporating multi-period allocation, transshipment between MCs, capacity sharing and mobile units. We develop a mathematical model that minimizes the total risk of unvaccinated population taking into account both susceptibility rate and exposure risk to categorize the priority groups. Various parameters including the availability of vaccine packs and pack sizes, capacities of MCs, mobile units, and transshipment network are used for improving the allocation decisions.

The remainder of the paper is organized as follows. Section 2 provides a comprehensive review of relevant analyses on vaccine allocation and distribution. Section 3 discusses how the proposed vaccine allocation systems work. Section 4 presents the mathematical model along with the solution approach which integrates a multi-period model with capacity sharing, cooperation and mobile units. The state of Victoria in Australia serves as the case study for this research in Section 5. Followed by the discussion of the findings in Section 6, Section 7 concludes the paper and addresses future research opportunities.

2. Literature review

While developing new vaccines in recent decades has been a significant achievement, vaccine supply chain-related issues such as shipping, storing and distributing vaccines effectively continue to be major challenges for health authorities (Yang et al., 2021; Emu et al., 2021). Pandemics are different from a typical disruption in supply chains in terms of the scope (global vs local) and in terms of dramatic shifts in demand and supply. Pandemic vaccine supply chains and typical vaccine supply chains share a number of features; however, the main difference between the two is the fact that in a pandemic vaccine supply chain, governments procure vaccines from manufacturers to ensure people have quick and equitable access to vaccines. As Duijzer et al. (2018) suggested, a vaccine supply chain has four main components and these are product, production, allocation, and distribution. These components hold true in a pandemic vaccine supply chain as well. In the product stage the important questions to ask are: firstly, which vaccine should be selected?; and secondly, what is the combination of virus strains in a vaccine? (Wu et al., 2005; Robbins et al., 2014). In production stage the quantity and the timing of the vaccine production are determined and this stage is also characterized by vaccine pricing strategies (Kazaz et al., 2016; Cho and Tang, 2013; Eskandarzadeh et al., 2016) and supplier selection decisions (Niu

et al., 2020; Federgruen and Yang, 2008). The production stage is a long process and yield uncertainties are inevitable which is the main reason for insufficient vaccine supplies in the market.

The first two components of the vaccine supply chain proposed by Duijzer et al. (2018) are mainly the focus of health and manufacturing domains, respectively. Our paper sits at the intersection of allocation and distribution components at the operational level given the fact that the proposed model incorporates allocation component. This is characterized by allocating vaccines to medical centers and distribution component through capacity sharing and transshipment by mobile units. Due to the fact that many countries have already begun inoculating their citizens using approved vaccines, the need to optimally allocate and distribute the produced vaccines becomes an urgent necessity. Having said that, and due to the importance of these two components of the vaccines supply chain, they are discussed separately in the following sections.

ABS-AJG 2021 ranking was used to extract high quality and high relevant journal articles (Chartered Association of Business Schools, 2021). ABS-AJG provides researchers with access to high quality research. All journals with the rankings 3, 4, and 4* on the topics 'Operations and Technology Management' and 'Operations Research and Management Science' were identified. In addition to the above list, the transportation research journals (Parts A, B, D and E) were included. This guarantees the focus is on the top quality journals that cover logistics and transportation operations. In the next step, keywords, namely 'vaccine', 'vaccination', 'pandemic', and 'COVID-19' were deployed to search relevant information in the title and article keywords for studies published in the last 20 years (2002–2021) in Scopus database. The final chosen articles appear in Tables 1 and 2.

2.1. Vaccine allocation

An optimal allocation strategy for a scarce vaccine is an effective way to contain a pandemic (Longini et al., 2004). The main questions in the allocation stage are who should be vaccinated and how the allocation should be done. These are difficult questions to answer due to the inadequate and uncertain supply of vaccines especially in the case of an unexpected outbreak and the existence of various competing priority groups. Since the supply of the vaccine is limited, it is critical for governments to prioritize and allocate a vaccine based on the vulnerability of certain populations groups (Tavana et al., 2021). Brandeau et al. (2003) posit that a range of factors such as the infection prevalence and incidence, population size, and characteristics of prevention programs imposed by governments affect the optimal resource allocation in a pandemic. The allocation stage is quite unique in the vaccine supply chain. Unlike a typical supply chain, in an allocation stage of vaccine supply chain, end consumers do not pay for the product in most cases so they wield little or no power in allocation-related decisions (Duijzer et al., 2018).

Allocation decisions are usually made at higher levels and while such decisions at global levels are based on contracts between vaccine providers and governments or agreement between countries, allocation decisions within the countries' borders are based on stage and severity of an epidemic (Emu et al., 2021). What makes the allocation stage in the pandemic vaccine supply chain more complicated is the conflicting goals of the ethical issues such as equity and the effectiveness of vaccine allocations (Enayati and Özaltın, 2020). This seems to be inevitable considering two widely accepted policies to allocate vaccine in a pandemic supply chain: pro-rata and prioritizing policies. In practice, the pro-rata policy is politically favorable because it is simple and minimizes any controversy (Araz et al., 2012). For example, the current allocation policy used by the Centers for Disease Control and Prevention, the US vaccine-dispensing body, during a flu epidemic is to use a pro-rata policy in which the vaccines are allocated based on the size of a region's population. In effect, vaccines might be allocated to regions with no demand while regions in need do not receive a vaccine (Larson and Teytelman, 2012). Despite the importance of equity in the pandemic vaccine supply chain (Delamonica et al., 2005; Jean-Jacques and Bauchner, 2021), only very few studies which consider equity in a form of mathematical modeling. This might be due to the challenges in dealing with equity such as the lack of a consensus on how equity is defined (Mitchell et al., 2009), and how to measure it (Stone, 2002). In the second policy, state-level and/or local government prioritizes the vaccine allocation among population subgroups. Despite the benefits of the pro-rata policy, research shows that prioritizing subgroups can reduce the spread of the pandemic more effectively (Araz et al., 2012; Matrajt et al., 2013). Nowadays, prioritization becomes more important in particular at the early stages of a pandemic outbreak as vaccine supply is quite limited during this period. For a vaccine prioritization system, various criteria are used to define subgroups such as age, degree of susceptibility, occupation, and geographical location. For example, Lee et al. (2012) developed a mathematical model to evaluate age-specific vaccination strategies for the 2009 H1N1 pandemic in Mexico. The key parameters in their model were mortality and contact rates, age distribution of the population, age-specific vaccine efficacy, and hospitalization rates. According to their findings, the optimal strategy is to allocate vaccines to young adults (20–39 yrs.) followed by school-age children. In a similar study, Medlock and Galvani (2009) found that optimal vaccine allocation is based on five outcome measures of deaths, economic costs, years of life lost, infections, and contingent valuation. According to their results, the best strategy for vaccine allocation is to prioritize schoolchildren and adults (30 to 39 yrs.). Tanner et al. (2008) used household parameters such as size and age to define subgroups. They found that these parameters played an important role in developing optimal vaccination allocation strategies.

Goldstein et al. (2012) use mixed factors of age and the degree of vulnerability to define priority groups. They investigate the optimal vaccine allocation in two groups. The first group includes adults with high risk of mortality while the second group includes school-age children due to their role in transmitting virus to their parent and consequently to the wider community. Their analysis shows that in case of a pandemic and in order to minimize the total number of mortalities, school-age children should be given the highest priority. In another study, Matrajt et al. (2010) use a mathematical model to allocate vaccine to two groups: one group with high transmission levels and the other group with high risk in two geographical regions of developed and developing countries. The results indicate that the optimal allocation strategy changes depending upon the status of a pandemic. They argue

Table 1

Literature review on the allocation stage of the vaccine supply chain.

Authors	Objectives	Research method	Priority groups	Variables	Findings
Buccieri and Gaetz (2013)	Using the utility principle and the equity principle to allocate the vaccine to certain people	Surveys and interviews	Homeless and Underhoused Individuals	Epidemiology of the spread of disease, demographic factors, fear of infection, lack of concern, access to community-based clinics, access to a regular doctor, promotional campaign	Prioritizing homeless individuals meets both utility and equity principals. Such prioritization can reduce the chance of infection to members of society.
Chen et al. (2020)	To find the optimal allocation of COVID-19 vaccines to multiple priority groups with limited resources	Use of SAPHIRE simulation model	Five priority groups	Number of susceptible and exposed individuals in each group, population size, transmission rate	Two allocation policies, namely static and dynamic were developed to minimize the number of infections or deaths. Static policies could achieve less infected cases (when younger groups are given priority) and deaths (when older groups are given priority). In dynamic policies, the priority should be given to older groups and then to younger ones.
Davila-Payan et al. (2014)	To investigate the factors which affect the pandemic vaccination coverage	Regression analysis	High-risk adults and children	State campaign information and state characteristics, preparedness funding, demographics, preventive behavior, surveillance data, and providers	Positive association between school clinics programs and two factors of a. children vaccine coverage and b. increased proportion of administered doses. Positive association between the coverage for high-risk adults and the shipments of vaccine to "general access" locations.
Goldstein et al. (2012)	To prioritize allocation of vaccine during a declining epidemic	Optimization model	Age and degree of vulnerability	Mortality risk, vaccine efficacy, medical conditions,	The analysis shows that in case of a pandemic and to minimize the total number of mortalities the school-age children should be given the highest priority.
Huang et al. (2017)	To allocate different types of vaccine while maximizing geographic equity across 189 Texas counties in the USA	Optimization model	Five priority groups (age, pregnant women, infant caregivers and adults at high risk)	Information about priority groups and geographical regions	The findings indicate that a proportionally fair allocation of discretionary cache would maximize the coverage of priority population in the countries hence, maximizing geographic equity.
Mamani et al. (2013)	Inefficiency in the vaccine allocation due to interdependencies between geographical regions	Mathematical model	none	Quantity of order and distribution in one country, the number of secondary infections in each country	The authors suggest contractual mechanism to reduce the inefficiencies in vaccine allocations

Table 1 (*continued*).

Authors	Objectives	Research method	Priority groups	Variables	Findings
Teytelman and Larson (2013)	To allocate limited vaccine to the US states to contain an influenza outbreak	Heuristics	none	Consider pandemic status in geographical regions based on real-time data in order to allocate vaccine	Considering the latest status of regional pandemic waves can significantly reduce the number of infections in the whole country
Uribe-Sánchez et al. (2011)	To help strategies cope with influenza pandemic in four regions in Florida, USA	Simulation-based optimization model	none	Morbidity, social distancing, and mortality	The proposed model is able to re-allocate resources remaining from the previous allocations which means better resource utilization.
Yarmand et al. (2014)	To contain the epidemic in multiple locations	Two-stage stochastic linear program (2-SLP)	Geographical regions	Population of region, attack rate, doses of vaccine	The reduction of vaccines doses and the attack rate. Also, since stage II is based on the outcome of stage I vaccination it is possible to more efficiently redistribute vaccine doses after stage I.
Govindan et al. (2020)	To develop a decision support system to classify community members and mitigate the epidemic outbreaks	Fuzzy inference system (FIS)	Four groups based on age, pre-existing diseases, risk level of their immune system	Age, pre-existing diseases, fever, tiredness, and dry cough	The validation stage using data shows the effectiveness of the proposed decision support systems.
Li et al. (2018)	To compare vaccine allocation strategies based two sets of information	Agent-based simulation	none	Individuals with certain states such as being susceptible, exposed, hospitalized, etc. Three levels of populations: community, peer groups and household.	The attack rate wanes when both population and vaccine inventory information are used. This leads to a reduction in the amount of inventory left over.
Biggerstaff et al. (2015)	To assess the impact of different vaccine plan in influenza pandemic	Simulation-based scenarios	Priority is given to the individuals who received the first dose	Vaccination coverage, clinical attack rates, case hospitalization ratios, case fatality ratios, , various starts of vaccination programs, vaccine effectiveness, and dose administration rate	Among various variables, the start date of vaccination has the highest impact. The administration rate and the effectiveness of vaccine did not have impact same as the start time of vaccination. Also, the case hospitalization, case fatality ratios, and clinical attack rate had the highest influence
Foy et al. (2021)	To compare vaccine allocation strategies based on age priority groups and non-pharmaceutical interventions	Mathematical Simulation	Eight priority groups 0–10, 10–20, [. . .] 60–70, 70 years	Vaccine efficacy, target coverage, rollout speed, immunity types	Prioritizing older individual would lead to the highest reduction in deaths regardless of the variables in the model such as vaccine efficacy, target coverage etc.
Rao and Brandeau (2021)	To control infectious disease, and minimize deaths, new infections, life years lost or QALYs	SIR (Susceptible, Infectious, or Recovered) model	Two priority groups ⟨65 with low morbidity and⟩ = 65 with high morbidity	Infection duration, infection severity, infected fatality ratio, death rate, expected life years lost	Prioritizing young individuals to minimize new infections and old individual to minimize death, life years lost or QALYs
Roy et al. (2021)	To disseminate vaccines among zones	linear optimization model	Geographical zones	Infection ratio, population density, susceptible count and infection ratio as well as transportation costs	The proposed model allocates vaccines efficiently and in the meantime prevents geographical zones experiencing resource starvation.

Table 2

Literature review on the distribution stage of vaccine supply chain.

Authors	Objectives	Research method	Variables	Stationary or Mobile DC	Findings
Halper and Raghavan (2011)	To maximize the service provided by mobile facilities	Routing problem	Demand service by each route, cumulative rate of demand	Mobile	The proposed heuristics show optimal routes for mobile facilities especially when demand changes over time.
Ramirez-Nafarrate et al. (2015)	To minimize the waiting time and travel distance to optimize the vaccine distribution	Genetic algorithm	Arrival rate to the point-of-dispensing sites (PODs), number of servers and census track assigned to POD	Stationary	While the proposed model generates output comparable to other similar approaches it is also able to explore a range of alternatives in case the resources are not sufficient to meet the performance objectives.
Araz et al. (2012)	Geographic prioritization of distributing pandemic influenza vaccines	Mathematical model	Mortality rate, social contact, infectious and incubation periods, transmission probability and location	unknown	In case vaccines are unavailable at late stage of pandemic it is recommended to prioritize those areas that are expected to have the latest waves of transmission.
Lee et al. (2013)	To identify the vaccine optimal location for vaccine distribution centers using RealOpt tool	SEPAIR six-stage model	Use of six stage of SEPAIR model: susceptible; exposed; infectious; asymptomatic; symptomatic; recovered	Stationary	Challenges and the benefits of RealOpt tools are discussed.
Aaby et al. (2006)	To optimize the allocation of vaccine distribution centers	Simulation models, capacity-planning and queuing models	Arrival rate, time spent for vaccination, MC capacity, served residents, staff number	Stationary	The proposed models were validated using real data.
Rachaniotis et al. (2012)	To minimize the total; number of infections	Scheduling problem	Number of susceptible and infected individuals, processing time, size of subpopulation	Mobile	The optimal schedule using mobile facility could significantly outperforms random scheduling.
Emu et al. (2021)	To select optimal distribution centers considering two factors of priority and distance	Optimization model (PD-VDM)	Total population to be vaccinated, number of DCs, DC capacities, priority levels	Stationary	The efficiency of the proposed model was shown using real data.
Enayati and Özaltın (2020)	To optimally distribute the vaccine in heterogeneous population	Non-linear optimization problem	Contact rate, group size, infectiousness of infected individuals, infectiousness of exposed individuals, recovery rate, vaccine coverage	Stationary	The group-specific transmission dynamics such as geographic location and age play an important role in the optimal allocation of influenza vaccine.
Larson and Teytelman (2012)	To analyze the effect of timing on the vaccine distribution	Mathematical model	Susceptibility, infectivity, and activity levels	Stationary	Vaccines must be administered well before the pandemic reaches its peak. In allocating vaccine, factors such as stage of pandemic in geographical regions should be taken into account.

Table 2 (*continued*).

Authors	Objectives	Research method	Variables	Stationary or Mobile DC	Findings
Dessouky et al. (2013)	To optimize the facility location and vehicle routing decisions in large-scale disaster relief	Mathematical modeling	Population size, distance, number of facilities and vehicle, vehicle capacity	Stationary	It is shown how the proposed model is considered in an anthrax emergency.
Matrajt et al. (2013)	To optimize vaccine distribution in a group of cities	Mathematical model	Illness attack rate, recovery rate, fraction of symptomatic, contact rates, vaccine efficacies, probability of transmission	unknown	The results indicate that the optimal allocation strategy changes depend on the status of the pandemic. They argue that children as a high transmission group should be given the highest priority during the early stages of the pandemic. This would help to break the transmission cycle early on. However, the priority group will shift to the high transmission group once too many people have already been infected.
Brown et al. (2014)	To explore redesigning the vaccine supply chain in Benin through adding freezer and refrigerators to the chain	HERMES simulation model	Labour, storage, transportation, and building costs	Stationary	Both capital and operating costs were reduced by eliminating redundancies in locations' personnel, equipment, and routes.
Ceselli et al. (2014)	To optimize the distribution of vaccine	Mathematical problem: Generalized Location and Distribution Problem	Types and number of vehicles, distance between nodes, capacity and number of distribution center	Mixed	The proposed approach outperforms the existing methods with higher levels of flexibility
Gamchi et al. (2021)	To minimize the social cost and the cost of vehicles used in controlling the spread of infectious decease	vehicle routing problem	Number of susceptible, infected and recovered individuals, transmission fate, distance, vehicle capacity, vaccine doses	Stationary	Test problems served to assess the performance of the proposed model.
Goodarzian et al. (2021)	To design a sustainable-resilience health care network during the COVID-19 pandemic	Mathematical problem: MILP	Quantity of transported medicines, inventory level	Unknown	The impact of transportation cost on social responsibility of staff and total cost of the model.

that children constituting a high transmission group should be given the highest priority at the early stage of a pandemic. This would help to break the likelihood of transmission at the initial stages of a pandemic. However, the priority group will shift to the high transmission group once too many people have already been affected. Buccieri and Gaetz (2013) combined the utility and equity principles in allocating vaccines. Utility principle states that resources should be utilized in order to provide the maximum health benefits to society; hence, emergency and health care workers should be given high priority because of their crucial role in ensuring that society functions as smoothly as possible. Based on age and pre-existing disease, Govindan et al. (2020) consider four priority groups with different risk levels of immune systems. A decision support system was proposed to manage the vaccine demand and reduce the number of infected people. Persad et al. (2020) argue that three groups of individuals should be given priority in vaccine allocations: people in high-risk occupations; health care workers; and people with high-risk conditions. They argue that the vaccine allocation needs to recognize ethical principles such as preventing harm and inoculating disadvantaged people. Deo et al. (2020) consider equity and fairness in allocating the COVID-19 vaccine. They propose a multi-parameters framework for vaccine distribution to prioritize vaccine allocation based on age, co-morbidities, profession, and income. McMorrow et al. (2019) use a range of risk factors to allocate influenza vaccine in low- and middle-income countries. The risk factors include morbidity and mortality rates, and prevalence of risk conditions for each country. According to their results, the highest rate of averted hospitalization per 100,000 belong to inoculated and the highest rate of averted deaths concerned adults with HIV, pregnant women, and individual with tuberculosis. The highest rate of averted death belonged to individuals who were 65 years of age or older.

Mamani et al. (2013) highlight the inefficiencies in the vaccine allocation and these are due to the interdependent risk of infection across borders. They argue that the vaccine decisions such as the quantity of order and distribution in one country influence the size of the outbreak in other countries. To reduce such inefficiencies, they suggest contractual mechanisms and their results confirm that the contract prevents millions of influenza cases. They also show that a lack of coordination would lead to excess vaccines in some regions but shortages in others. Using measures of mortality, morbidity, and social distancing, Uribe-Sánchez et al. (2011) develop a simulation-based optimization model to generate mitigation strategies for the influenza pandemic in four regions in Florida, USA. The proposed model is able to re-allocate resources remaining from the previous allocations which results in greater resource utilization. Teytelman and Larson (2013) developed several heuristics for allocating limited vaccine to states in the US to contain an influenza outbreak. Rather than relying on the traditional deployment of a vaccine based on the size of the resident population, they considered pandemic status in each region based on real-time data in order to allocate vaccine. Their findings show that considering the latest status of regional pandemic waves in emergency planning can significantly reduce the number of infections throughout the whole country. Based on a two-stage vaccination policy Yarmand et al. (2014) developed a two-stage stochastic linear program (2-SLP) for an allocation vaccine problem with an ultimate aim of containing the epidemic in multiple locations. The policy resulted in the reduction of vaccines doses and attack rate. Also, since stage II is based on the outcome of stage I vaccination, it is possible to more efficiently redistribute vaccine doses after stage I. Huang et al. (2017) developed a model to optimize the allocation of different types of vaccine to five priority groups (i.e., 0–3 year-old infants, people aged between 4–24, pregnant women, infant caregivers and adults at high risk) while maximizing geographic equity. This is referred to as the provision of the same proportions of each vaccine type across 189 counties in Texas. The findings indicate that a proportionally fair allocation of discretionary cache would maximize two things: the coverage of priority populations in the countries and geographic equity. Davila-Payan et al. (2014) investigate the factors which affect the pandemic vaccination coverage within two groups of high-risk adults and children. Using a multivariate linear regression, they found that the venue of vaccinations and providers have a positive association with the coverage rate in both groups.

With the aim to allocate the COVID-19 vaccine to different priority groups, Chen et al. (2020) used a SAPHIRE model with the epidemic data from New York City. They developed two allocation policies, namely static and dynamic and these minimize the number of infections or number of deaths. According to their findings, the static polices could achieve less infected cases (when younger groups are given priority) and death (when older groups are given priority). They recommend that in dynamic policies during the early days of a pandemic, the priority should be given to older groups and then to younger ones. Table 1 summarizes the literature on various allocation models for the vaccine supply chain.

2.2. Vaccine distribution

The distribution decisions determine how the vaccine should be delivered to the patient (end consumer) and revolve around the design of the supply chain and logistical decisions at the operational level. For example, this refers to the locations and capacities of medical centers, routing and scheduling for mobile facilities, staffing, and temperature-control logistics. However, a study by De Boeck et al. (2020) shows that research on vaccine distribution has been mainly done on strategic decisions. A vaccine supply chain is a multi-layered supply chain with many decision nodes and firms which makes the distribution in the vaccine supply chain more complicated (Duijzer et al., 2018). Reviewing the literature shows that reducing decision levels can curtail the overall costs and increase the availability of vaccines (Brown et al., 2014). For example, Assi et al. (2013) employed HERMES software (Highly Extensible Resource for Modeling Supply Chains) to model Niger's vaccine supply chain to compare the existing four-tier (central, regional, district, and integrated health center levels) with a modified three-tier structure (removing the regional level). They showed that by removing the regional level vaccine availability increased quite significantly and reduced supply chain logistics costs. In another study, Goodarzian et al. (2021) proposed a COVID-19 MILP model for a sustainable and resilient health care network that could, under conditions of uncertainty, incorporate major components of a supply chain. Their emphasize the impact of transportation costs on social responsibility of staff and total cost of the model. Masoumi et al. (2012) developed a supply chain network model for a perishable product which yielded equilibrium product supply chain flows and equilibrium product demands. Saif

and Elhedhli (2016) devised a cold supply chain model for vaccine to minimize the total cost of the cold supply chain and global warming impact which included refrigerant gas leakage and CO2 emissions. They discovered that the global warming effect could be significantly reduced with a small increase – and in some cases virtually no increase – in cost. Biggerstaff et al. (2015) put together a model to investigate the impact of various scenarios on the number of hospitalizations and deaths in an influenza pandemic. These scenarios include vaccination coverage, different vaccination programs, number of vaccine doses administered per week, and levels of vaccine effectiveness. Their results show that the start of vaccination program (before a pandemic) has the highest impact on both the number hospitalization and deaths. In a similar study, Enayati and Özaltın (2020) proposed a non-linear optimization problem and how an influenza vaccine should be distributed. They showed that the group-specific transmission dynamics such as geographic location and age play an important role in the optimal distribution of influenza vaccine units.

Using a mixed-method of interviews and survey method, Privett and Gonsalvez (2014) show that the lack of coordination among different actors, layers, and functions of pandemic vaccine supply chain is the first challenge that senior managers of health pharmaceutical supply chain face. To a great extent, the issue is due to conflicting priorities of different actors (Yadav, 2010) and too many global health systems that are not well structured and informal alliances governed in health supply chain (Fidler, 2007; Sridhar and Batniji, 2008). Effective and real time communication between vaccine providers and health authorities plays an important role in improving coordination. Fitzgerald et al. (2016) emphasized good coordination between public health programs and pharmacies for successful vaccine distribution plans in 53 US jurisdictions. Though a significant proportion of all 53 jurisdictions (88.7%) included pharmacies in the pandemic vaccination programs, the authors argue that formalized agreement need to be established between public health departments and pharmacies to: firstly, enhance vaccine distribution plans; and secondly, maximize the utilization of pharmacies during a pandemic.

Arifoğlu and Tang (2021) proposed an incentive program to coordinate a pandemic vaccine supply chain for both sides of demand and supply. On the demand side, there exist individuals who behave on a self-interested basis to participate in vaccination programs. On the supply side, there are vaccine manufacturers who aim to maximize their profits with some levels of uncertainty. The authors show how on the demand side incentive programs create a negative incentive to control the demand in case of limited vaccine supply and vice versa. On the supply side, the incentive programs subsidize the manufacturers to supply vaccine in large amounts but penalizes them for failing to do so. Lydon et al. (2015) assess the coordination efforts in the vaccine supply chain at a higher level and propose outsourcing some logistics operations to the private sector. Their analysis shows the theoretical benefits of outsourcing. Using the mixed integer programming (MIP), Yang et al. (2021) suggested a new algorithm to formulate the distribution network design for childhood vaccines in four African countries. The proposed MIP-based disaggregation-and-merging algorithm is able to yield optimal solutions when the network is small and the minimum cost is verifiable. For large problems that cannot be solved by MIP commercial software, the algorithm yields a reasonable solution requiring only very short computation time. Matrajt et al. (2013) used a airline transportation network to optimally distribute limited doses of a vaccine within a network of 16 South Asian cities. They combined a mathematical model with a genetic algorithm to minimize the infection attack rate. Under their proposed vaccination strategy, the attack rate dropped significantly. Also, they found those strategies which involved cooperation among cities in distributing vaccines resulted in lower attack rate (17% lower) compared to the strategies solely based on equal distribution of vaccines in the cities.

Using two factors of priority and distance, Emu et al. (2021) propose a clustering-based solution to optimally distribute the available COVID-19 vaccines. They compare their proposed model with three different models which included either one or no optimization constraints. The model provides an optimal solution that has the flexibility to consider different demographic variables.

While vaccines are traditionally administered in medical centers, using mobile units for vaccination has been considered for two main reasons. The first is the geographical dispersion of the population to be vaccinated. Using mobile vaccination units play a vital role in geographically dispersed populations and especially in rural and remote areas (Muckstadt et al., 2021; Yang and Rajgopal, 2021). The second reason is the resource and capacity limitation (i.e., number of medical centers, vaccine supply) in vaccine allocation and distribution. We argue that using mobile units can enhance the capacity of vaccine administration. In fact, reviewing the literature shows that using mobile units for vaccination is favored mainly because it provides access to remote/rural areas and convenience for many people (Turcotte et al., 2021). For example, examining the factors relating to vaccine, Liao et al. (2020) found that using mobile units is a convenient alternative which can significantly increase the vaccination probability and promote vaccination uptake. Referring to extra supply, a medical center is able to serve a limited number of neighboring medical centers in proximity using mobile facilities. Halper and Raghavan (2011) employed a routing problem to meet the demand in nodes of a network using mobile facilities. Abbasi et al. (2020) reported the significant impact of medical centers' capacity on the transmission of a virus in a community, and hence they proposed employing a mobile unit to provide more support for those medical centers where high demand was evident. Table 2 summarizes the extant literature on the distribution stage of the vaccine supply chain.

3. Operationalization and contributions

By August 2021, there were 110 vaccines in clinical development according to WHO (2021b). While countries around the world have already started inoculating their population, new cases of COVID-19 are rising globally as new variants circulate widely. Hence, there is an urgent need to optimally allocate and distribute the produced vaccines to curb the disease's spread. To address this need, we propose the vaccine allocation system shown in Fig. 1.

The system commences by estimating the number of people willing to be vaccinated in the catchment area of each medical center. Individuals are required to complete a form on an online booking system (OBS) providing demographic information on their
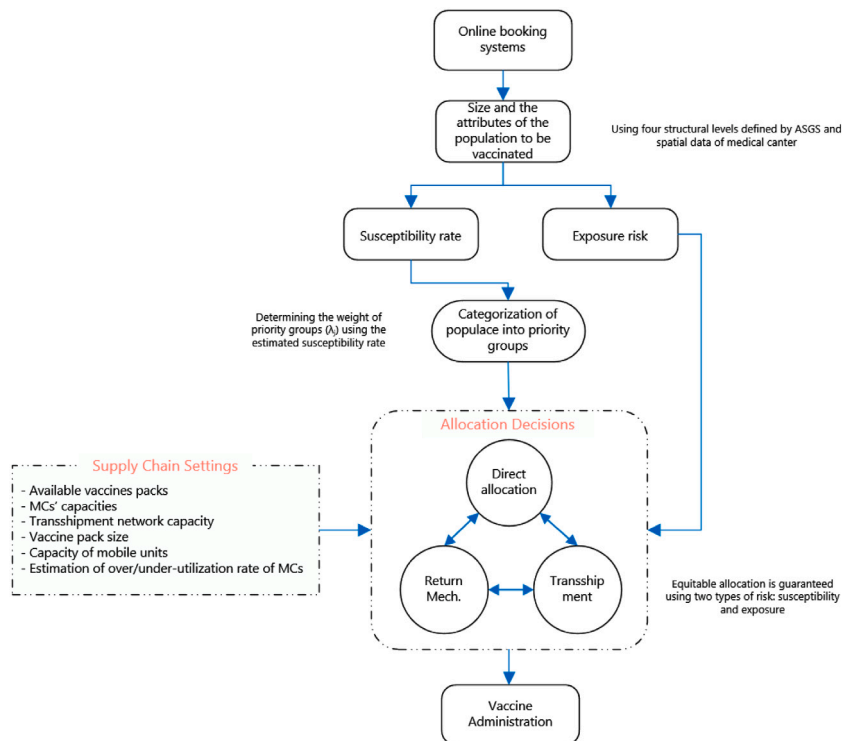
Fig. 1. Vaccine allocation operational process.

age, gender, occupation, and pre-existing health conditions. In the next step, a susceptibility rate is computed for each priority group based on the data collected through OBS. We define susceptibility rate as a state of physical well-being that is in danger of deteriorating due to an infectious disease. The susceptibility rate serves to categorize all eligible individuals into priority groups. In computing the susceptibility rate various parameters may be used including age, occupation, and pre-existing health condition (Chen et al., 2020; Goldstein et al., 2012; Huang et al., 2017; Govindan et al., 2020). This stage would lead to clustering the population into a number of priority groups ranging from the least susceptible group to extremely susceptible group. Categorization of priority groups forms the first input into the allocation decision stage. Meanwhile, the literature shows that geographical locations with higher population density are at higher risk of exposure to infectious diseases, hence, people who are living in these regions should be given greater priority to be vaccinated in order to contain the pandemic. As the second input to the allocation decision stage in the proposed allocation system, exposure risk is defined as the probability of community transmission. This is calculated as the ratio of demand in a catchment area to the total demand for the same priory group in all catchment areas. The characteristics of the supply chain also play important roles in any vaccine allocation modeling which form the third data input to the allocation decision stage. The procured vaccines are shipped and stored in distribution centers (source nodes) in capital cities. The available vaccine pack distributed to source nodes along with the size of the vaccine pack are important factors that can shape the optimal allocation decision. Research shows that the size of the vaccine packages wields a significant impact on the duration of vaccine administration and the number of transshipped vaccines (Abbasi et al., 2020). Then using specialized vehicles, cold storage boxes containing vaccines are sent to medical centers (sink nodes) to vaccinate individuals. Medical centers might be over- or under-supplied. For this reason, vaccine transshipment between medical centers is included in the proposed model to effectively meet the needs of all medical centers.

Using three data inputs discussed above and applying a mathematical model, the allocation decisions stage aims to simultaneously optimize three sets of mechanisms: (i) direct allocation of vaccines from DC; (ii) indirect allocation through transshipment among MCs; and (iii) mechanisms to return unused vaccines to the DC to ultimately minimize the total weighted risk of unvaccinated populations.

This study makes the following contributions within the domain of the pandemic supply chain.

Proposing a multi-period capacity allocation model: It is obvious that allocation decisions for an ideal vaccine allocation model should be made throughout the entire planning horizon. However, the current computational power is unable to cope with the complexity of a vaccine allocation model even for a short planning horizon (e.g., 60 days) of a mid-size city. At the other extreme, a single-period model is the most simplified approach to address the actual problem which results in an unsatisfactory solution because demand and resource capacities are ignored in future periods. As a theoretical contribution, this study proposes a multi-period vaccine allocation model as well as a novel solution approach which is flexible enough to be used with any computational power. This would help the

Table 3
Notations and definitions.

Notation	Definition
Sets and indices	
$\mathscr{R}$	The set of priority groups, $\mathscr{R} = \{1, 2, \ldots, R\}$.
$\mathscr{D}$	The set of demand points (medical centers), $\mathscr{D} = \{1, 2, \ldots, D\}$.
Parameters	
P	The number of vaccine units in each package (lot size).
d_{ij}^t	The number of unvaccinated people in priority group $j \in \mathscr{R}$ who are booked to receive the vaccine in medical center $i \in \mathscr{D}$ in period t.
λ_j	The weight of a priority group $j \in \mathscr{R}$. Priority groups with higher weight receive priority for getting the vaccine ($\sum_{j=1}^{R} \lambda_j = 1$) .
C_i	The capacity of a medical center $i \in \mathscr{D}$ to administer the vaccine per period of time.
M	A big number.
ϵ	A very small number (e.g., 0.00001).
γ	The minimum difference between the weights of each pair of priority groups: $\gamma = min(\lambda_{j-1} - \lambda_j)$.
δ_{ij}	The travel time between medical centers $i \in \mathscr{D}$ and $j \in \mathscr{D} \setminus \{i\}$. $\dot{\delta} = max(\delta_{ij})$.
$\mathscr{K}$	The total available travel time for vehicles to transship vaccines between medical centers per day assuming that each vehicle works 8 h per day. For example if there are 5 vehicles available in the transshipment network, $\mathscr{K} = 5 \times 8 = 40$.
η_{ij}	This binary variable becomes 1 for at most m number of medical centers with non-zero demand which are at the closest distance from medical center $i \in \mathscr{D}$ and they are linked for transshipment of vaccines. $j \in \mathscr{D}$ is the index of those medical centers.
Decision variables	
α_i^t	The number of vaccine packages allocated to demand points (i.e., medical centers) $i \in \mathscr{D}$ in period t.
$\dot{d}_{ij}^t$	The number of unvaccinated people in priority group $j \in \mathscr{R}$ in medical center $i \in \mathscr{D}$ in period t.
S^t	The number of vaccine packages which are available in each time period (t) in the DC given that DC receives the Q vaccine packs from the federal government in each period t.
x_{ij}^t	The number of vaccine units administered to unvaccinated people at medical center $i \in \mathscr{D}$ who are in priority group $j \in \mathscr{R}$ at period t.
y_{ij}^t	The number of vaccine units transshipped from medical center $i \in \mathscr{D}$ to medical center $j \neq i \in \mathscr{D}$ in period t.
z_{ij}^t	The binary decision variables to define if a transshipment from medical center $i \in \mathscr{D}$ to medical $j \neq i \in \mathscr{D}$ has taken place in period t.
ϱ_i^t	The number of unused vaccine units in medical center $i \in \mathscr{D}$ which are returned to the DC due to no capacity or demand in period t.
$\xi_i^{in,t}, \xi_i^{out,t}$	The binary decision variables to determine transshipment (in or out) in medical center i in period t.

model to further reduce the residual risk of unvaccinated people compared to the single-period approach. Furthermore, the actual administrating horizon is expected to be significantly decreased.

Replenishment policy: In a similar study, Abbasi et al. (2020) used a base-stock level policy in which a fixed level of vaccine supply became available in each period. The proposed model in this paper employs a (T,Q) inventory replenishment policy for DC. Such a policy is more realistic and suitable for Australia because its federal government considers a daily or weekly quantity of vaccine for all five states and territories regardless of the number of returned vaccines in the previous period. Moreover, the returned vaccine units are disregarded in the single-period model whereas they are added to the capacity of the next period in the proposed multi-period allocation model.

Embedding capacity sharing and cooperation mechanisms: It is quite likely that capacity of medical centers would be the most restrictive constraint in the administering process. Such situations become more prevalent at the later stages of vaccine administration in which the chance of having MCs with no or high demand would increase. This would lead to inefficiencies in the vaccine allocation model. To deal with such problems, as a practical contribution, a cooperation and capacity sharing mechanism is included in the proposed model. Through such mechanisms under-utilized MCs would be able to offer their capacities to the MCs with high demand. The mechanism provides the opportunity for demand to be redistributed among eligible adjacent medical centers, which ultimately improves the overall efficiency of the allocation model.

Embedding mobile units: Health authorities aim to employ all possible means and strategies to enhance the efficiency of vaccination operations. The role of mobile vaccination units becomes more prominent given the geographical distribution of the population (Muckstadt et al., 2021; Halper and Raghavan, 2011). However, as shown in Table 2, the majority of research on vaccine distribution uses stationary vaccine distribution units. As a practical contribution, mobile units are included in the proposed model here to diminish the bottlenecks caused by the capacity constraints.

4. Mathematical model and solution approach

In this section, to address the aforementioned requirements of a vaccine distribution network in a pandemic, we propose a vaccine allocation model in which the decisions are made over multiple periods. We also improve the efficiency of the proposed model by using the capacity sharing mechanism and employing the mobile units. Table 3 presents the notations which are used in the multi-period allocation model.

In any pandemic, one of the important aims for health authorities is to vaccinate the whole populace within a target horizon. For the majority of countries dealing with a sudden pandemic outbreak, although the vaccine allocation policies may not be the same,
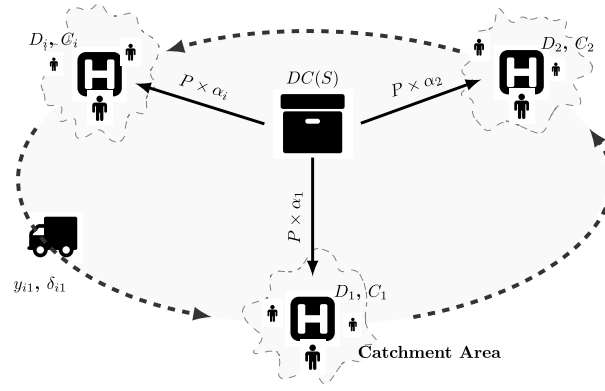
Fig. 2. Schematic overview of vaccine distribution network.

having excellent operational efficiency and service levels (e.g., coverage) supersedes any attempts to minimizing cost inefficiencies regarding the vaccine distribution network. Therefore, the key objective of the proposed allocation model is to effectively distribute the vaccines, whereby the most vulnerable population categories with a higher susceptibility rate receive more attention. In addition to considering the higher priority for the high-risk groups, it is crucial to factor in the exposure risk as one of the underlying reasons that influences the degree of community transmission. In other words, for the same risk group, a larger population in an area leads to higher risk of exposure, so the system should give higher priority for allocating the vaccine to this category.

The schematic overview of a vaccine distribution network is presented in Fig. 2. In the single-period model designed by Abbasi et al. (2020), the distribution center (DC) is assumed to employ the base-stock policy whereby in each period the base-stock level of S becomes available to be distributed among the vaccine administering sites. However, we assume a (T,Q) inventory replenishment policy for DC as it is more realistic for the vaccine allocation model. For example, the Australian federal government generally considers a daily/weekly fixed quantity of vaccine for each state. Therefore, irrespective of the number of vaccine units which may be returned from medical centers to the DC in the previous period (ϱ_i^{t-1}), DC still receives the same number of vaccine packs from the federal government on a timely basis.

Depending on the government decision at the state level, hospitals, medical centers, or even general practitioners may be nominated to vaccinate individuals. In this study, we assume that i number of medical centers are assigned to administer the vaccines. Note that each medical center has a limited capacity (C_i) to provide the administering services. For each medical center i, the catchment area determines the assigned demand (D_i). In the Case Study section, we delineate the mechanism that we consider to select the catchment area for each medical center.

Given that vaccines are distributed in packs with the pack size of P, each medical center i receives $P \times \alpha_i^t$ vaccine units in period t. However, since this value ($P \times \alpha_i^t$) is not necessarily divisible by the demand of medical center i, an effective allocation model should encapsulate a mechanism to re-distribute the remaining of vaccine units in each period to further decrease the total risk of unvaccinated population. As depicted in Fig. 2, the proposed allocation model includes a transshipment mechanism among medical centers to distribute the remaining vaccine units to other centers located in close vicinity and their demand has not been fully met in the same period. In this sense, if the travel time between the medical centers i and 1 would be δ_{i1}, the number of transshipped vaccine units between these centers is denoted as y_{i1}.

Based on the stated requirements, we are now able to define the problem as how to develop an effective vaccine allocation mechanism whereby: (i) citizens receive the vaccine based on their exposure risk and susceptibility rating; (ii) the model supports distributing the vaccines in packs; (iii) transshipment strategy improves the operational efficiency of the distribution network, while not exceeding the transshipment capacity of the network; (iv) capacity of medical centers for administering the vaccines to residents living in a reasonable range of proximity from the medical centers is not exceeded; and (v) allocation decisions are made for a multi-period time window to deliver the highest operational efficiency. Next, the proposed mathematical model which is an extension of the study of Abbasi et al. (2020) is presented to address the aforementioned requirements.

$$\min \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{R}} (\lambda_j + \gamma \frac{d_{ij}^t}{\sum_{l \in \mathcal{D}} d_{lj}^t})(d_{ij}^t - x_{ij}^t) + \epsilon \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{D} \setminus \{i\}} \delta_{ij} y_{ij}^t + \epsilon \dot{\delta} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{D}} \varrho_i^t \tag{1}$$

$S.t:$

$$\sum_{j \in \mathcal{R}} x_{ij}^t = P \alpha_i^t + \sum_{j \in \mathcal{D} \setminus \{i\}} (y_{ji}^t - y_{ij}^t) + (\varrho_i^{t-1} - \varrho_i^t), \quad \forall i \in \mathcal{D}, t \in \mathcal{T} \tag{2}$$

$$d_{ij}^t = d_{ij}^t + \sum_{\tau=1}^{t-1} (d_{ij}^\tau - x_{ij}^\tau), \quad \forall i \in \mathcal{D}, j \in \mathcal{R}, t \in \mathcal{T} \setminus \{1\} \tag{3}$$

$$PS^t = PQ + \sum_{i \in \mathcal{D}} \varrho_i^{t-1}, \quad \forall t \in \mathcal{T} \setminus \{1\} \tag{4}$$

$$\sum_{i\in\mathscr{D}} \alpha_i^t \leq S^t, \quad \forall t \in \mathscr{T} \tag{5}$$

$$\sum_{j\in\mathscr{R}} x_{ij}^t \leq C_i, \quad \forall i \in \mathscr{D}, t \in \mathscr{T} \tag{6}$$

$$\sum_{i\in\mathscr{D}} \sum_{j\in\mathscr{D}\setminus\{i\}} z_{ij}^t \delta_{ij} \leq \mathscr{K}, \quad \forall t \in \mathscr{T} \tag{7}$$

$$\sum_{j\in\mathscr{D}} z_{ij}^t \leq M\tau_i^{out,t}, \quad \forall i \in \mathscr{D}, t \in \mathscr{T} \tag{8}$$

$$\sum_{j\in\mathscr{D}} z_{ji}^t \leq M\tau_i^{in,t}, \quad \forall i \in \mathscr{D}, t \in \mathscr{T} \tag{9}$$

$$\tau_i^{out,t} + \tau_i^{in,t} \leq 1, \quad \forall i \in \mathscr{D}, t \in \mathscr{T} \tag{10}$$

$$z_{ij}^t \leq \eta_{ij}, \quad \forall i \in \mathscr{D}, j \in \mathscr{D} \setminus \{i\}, t \in \mathscr{T} \tag{11}$$

$$x_{ij}^t \leqslant d_{ij}^t, \quad \forall i \in \mathscr{D}, j \in \mathscr{R}, t \in \mathscr{T} \tag{12}$$

$$y_{ij}^t \leq Mz_{ij}^t, \quad \forall i \in \mathscr{D}, j \in \mathscr{D} \setminus \{i\}, t \in \mathscr{T} \tag{13}$$

$$\alpha_i^t, x_{ij}^t, \varrho_i^t \in \mathbb{Z}^{0+}, \quad \forall i \in \mathscr{D}, \forall j \in \mathscr{R}, t \in \mathscr{T} \tag{14}$$

$$y_{ij}^t \geq 0, \quad \forall i \in \mathscr{D}, j \in \mathscr{D} \setminus \{i\}, t \in \mathscr{T} \tag{15}$$

$$z_{ij}^t \in \{0,1\}, \quad \forall i \in \mathscr{D}, j \in \mathscr{D} \setminus \{i\}, t \in \mathscr{T} \tag{16}$$

$$\xi_i^{in,t}, \xi_i^{out,t} \in \{0,1\}, \quad \forall i \in \mathscr{D}, t \in \mathscr{T} \tag{17}$$

$$\varrho_i^0 = 0, \quad \forall i \in \mathscr{D} \tag{18}$$

$$d_{ij}^1 = d_{ij}^1, \quad \forall i \in \mathscr{D}, j \in \mathscr{R} \tag{19}$$

$$S^1 = S \tag{20}$$

Objective Function: The objective function has three main components to manage the following three key operations of the allocation model:

Minimizing the weighted risk of unvaccinated population $(\sum_{t\in\mathscr{T}} \sum_{i\in\mathscr{D}} \sum_{j\in\mathscr{R}} (\lambda_j + \gamma \frac{d_{ij}^t}{\sum_{l\in\mathscr{D}} d_{lj}^t})(d_{ij}^t - x_{ij}^t))$:

In each period (t), the term $(d_{ij}^t - x_{ij}^t)$ signifies the number of unvaccinated people. The core function of the objective function for the vaccine allocation model is to minimize this term by allocating the vaccine packs directly from the DC as much as possible. However, to design an equitable allocation model, the weighted risk of unvaccinated population should also be considered. The designed weighting factor has two key elements: (i) *susceptibility* (λ_j), and *exposure risk* ($\frac{d_{ij}^t}{\sum_{l\in\mathscr{D}} d_{lj}^t}$). As explained earlier, depending on a number of parameters including age, occupation, etc. a risk group with higher weight should get more priority to receive the vaccine. Therefore, λ_j signifies the *susceptibility* of each risk cluster and it refers to the weight of priority groups. In the Case Study section, a basic method to determine the values of λ_j is provided.

Also the term ($\frac{d_{ij}^t}{\sum_{l\in\mathscr{D}} d_{lj}^t}$) is the probability of the community transmission. In a densely populated catchment area, it is more likely that people get exposed to infectious diseases. Therefore, the *exposure risk* of each priority group can be measured by the quotient of the demand of a particular catchment area and the total demand of all catchment areas for the same priority group. Given that the *susceptibility* factor of a risk priority group exerts a more significant influence in reducing the total risk of unvaccinated people compared to the *exposure risk*, we have incorporated a primacy coefficient ($\gamma = \min_{j\in\mathscr{R}}(\lambda_{j-1} - \lambda_j)$) to ensure that priority groups with higher weight of *susceptibility* receive greater attention to get vaccinated, and then the weight of *exposure risk* is taken into consideration. Note that the whole term of $\sum_{t\in\mathscr{T}} \sum_{i\in\mathscr{D}} \sum_{j\in\mathscr{R}} (\lambda_j + \gamma \frac{d_{ij}^t}{\sum_{l\in\mathscr{D}} d_{lj}^t})(d_{ij}^t - x_{ij}^t)$ is an indication of *Residual Risk* in the vaccine allocation model.

Transshipment mechanism ($\epsilon \sum_{t\in\mathscr{T}} \sum_{i\in\mathscr{D}} \sum_{j\in\mathscr{D}\setminus\{i\}} \delta_{ij} y_{ij}^t$):

Although reducing the residual risk of unvaccinated people through the direct shipment of vaccine units from the DC seems to be the most effective method, embedding the transshipment mechanism in the allocation model can assist to further minimize the residual risk. This mechanism is triggered by two events. First, if there is no demand for what remains of a vaccine pack in a particular medical center, the excess vaccine units can be re-distributed to centers in close proximity to further minimize the total residual risk of unvaccinated people. Second, if in a medical center there are unvaccinated people belonging to the higher priority groups, vaccine units can be shipped from other medical centers when no demand exists for these groups. Given that δ_{ij} is the travel time between medical centers, the model seeks transshipment opportunities where the least travel time is possible.

As direct shipping of the vaccine packs from the DC to medical centers and also transshipping the vaccines among medical centers are both included in the objective function, there is a need for another primacy coefficient to ensure that the direct shipping of vaccine packs receives higher priority compared to the transshipment mechanism. This coefficient ($\epsilon \leq \frac{min(\lambda_j)}{\dot{\delta}(P-1)}$ where $\dot{\delta} = max(\delta_{ij})$)

is adopted from Abbasi et al. (2020). Any given value for the ϵ which satisfies this condition causes the first component of the objective function (direct shipping) to receive higher priority compared to the second component (transshipment).

Return mechanism ($\epsilon \dot{\delta} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{D}} \varrho_i^t$):

For a small portion of vaccine units in a given period, it is possible that no viable option would be available to administer the vaccine. For example, assume that there are remaining vaccines in a medical center and there is no other medical center located in close vicinity with unmet demand. Another example would be the situation in which the capacity of medical centers is full and no transshipment capacity is available in the network. For these situations, we need a complementary mechanism to return the unused vaccines to the DC at the end of each period.

For each period t, a medical center i may return ϱ_i^t number of vaccine units to the DC. Note that the returning mechanism should be triggered when there is no opportunity to further decrease the residual risk through the direct shipping vaccine packs from the DC or transshipping the vaccines among the medical centers. Therefore, the primacy coefficient of $\epsilon \dot{\delta}$ ensures that the vaccines are returned to the DC if none of the developed allocation mechanisms can be used.

Constraints: Constraints (2) guarantee that in each period, the total number of vaccine units that can be administered in a medical center equals the number of vaccines received from the DC, plus the balance of the transshipped vaccines to/from all other medical centers, plus the difference between the number of returning vaccines to DC in periods $t - 1$ and t. This is one of the benefits of the multi-period design of a vaccine allocation model because the decision on number of returning vaccines are made over multiple period. Thus, it is likely that the model will be able to identify an opportunity to allocate a vaccine unit rather than returning it to the DC. Constraints (3) ensure that the actual demand of each period (d_{ij}^t) for each priority group in a medical center includes the estimated demand of the current period and the accumulated unmet demand of previous periods.

Constraints (4) limit the total available vaccine units in the DC for each period t to be the number of vaccine units that the DC receives from the federal government in period t plus the accumulated total number of returning vaccine units from all medical centers over the previous periods. Constraints (5) ensure that no more than the available vaccine packs in the DC can be allocated to the medical centers. Constraints (6) limit the number of vaccine units administered in each period in a medical center to the capacity of the same medical center. Constraints (7) prevent the total capacity of transshipment network to be exceeded, taking to account the total available vehicles and the travel time between the medical centers.

Constraints (8)–(10) ensure that each medical center acts as either a sender or receiver in the transshipment network. Constraints (11) limit the transshipment mechanism so that it is available for at most m number of medical centers with non-zero demand which are at the closest distance from a particular medical center. Constraints (12) guarantee that for each period, no more than a medical center's demand can be allocated from the DC. Constraints (13) specify that transshipment of vaccines only takes place when the corresponding route is available for transshipment. Constraints (14)–(17) define the domain of variables where the set of non-negative integers is denoted as $\mathbb{Z}^{0+}$. Constraints (18)–(20) specify the initial value of ϱ_i^0, d_{ij}^1, and S^1.

4.1. Solution approach

In a single-period setting, allocation decisions in each period are made in isolation from other periods. Although the single-period model provides a basis for a vaccines allocation model during a pandemic, we have identified a number of opportunities for improvement which result in a superior response plan. Details of the identified initiatives are explained in the following sections.

4.1.1. Solving a multi-period model

It would be more realistic to make the allocation decisions for each time period by considering the demand and available capacities of future periods. Therefore, we have developed a multi-period allocation model to address the myopic issues of the single-period model which leads to sub-optimal results. The issue in designing and implementing a multi-period allocation model is related to limitations in computational power. To clarify this issue, let us assume that the time needed to administer vaccines to a population is 60 days which is called Planning Horizon (PH). The current available computational power is unable to solve such a multi-period model for the entire planning horizon of a mid-size state such as Victoria. To address this issue, we have consulted a number of leading consulting companies which are active in providing solutions for large problems in the supply chain area. This led us to the following solution approach for the multi-period vaccine allocation model.

As depicted in Fig. 3, by conducting a pilot test, first, we need to establish the maximum Multi-Period Window (MPW) which can be solved using the available computational power. For example, in our case study, we have noted that MPW is 14 which means that our computational power (Intel Xeon CPU E5-2680 V3 @2.5 GHz and 64 GB RAM) is able to solve the multi-period problem with a maximum MPW of 14 days within a reasonable solution time. To strike a balance between myopic and hyperopic policies, we consider the following procedure. For one half of the MPW (e.g., 7 days), allocation decisions are made on a daily basis. Subsequently, to ensure that the profile of future demand is not ignored, mean of demand for the subsequent $\frac{MPW}{2}$ periods is considered for the period $\frac{MPW}{2} + 1$. This process continues until estimated demands for the second half of MPW are obtained. Using this method enables the model to consider both current and future demand profiles in allocation decisions for the current period. When allocations are made for the entire MPW period, we retain the results for the first $\frac{MPW}{2}$ and discard those of the second period. Then, the algorithm restarts for the next $\frac{MPW}{2}$ periods. When the algorithm progresses, if there are not enough number of $\frac{MPW}{2}$ periods available to the end of PH, the algorithm adjusts the second part of MPW for the remaining periods.

Since PH is not necessarily divisible by the $\frac{MPW}{2}$, having a number of remaining days at the end of phase (I) is possible. Note that allocations may not be completed at the end of PH and it may be extended for a number of periods to ensure that the entire
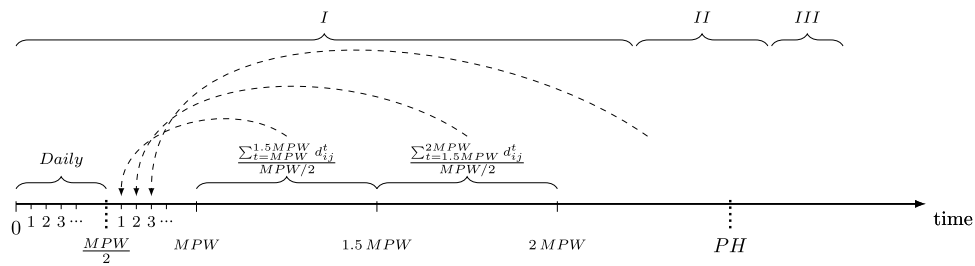
Fig. 3. Schematic overview of solution approach for solving the multi-period vaccine allocation problem with MPW.

population is indeed vaccinated. In this case, to make a decision as to whether a single-period or a multi-period model should be employed, the algorithm considers two crucial factors: (a) the remaining number of periods, and (b) the magnitude of unmet demand. In phase (II), if there is still an opportunity to solve the model in the multi-period mode, the algorithm continues in the multi-period setting. This process continues until phase (III) in which the algorithm shifts to the single-period setting and completes the allocation process until the value of unmet demand becomes zero.

4.1.2. Augmented multi-period model (capacity sharing and cooperation)

For the majority of vaccine allocation models, demand is generally higher than supply for the first stage of administering vaccines where many people book to receive the vaccine as soon as possible. However, this trend is reversed at a turning point during the administering horizon. From the turning point onward, in particular during the last third of the administering process, there are many medical centers with no demand whereas others are overwhelmingly busy with high capacity utilization rates. To improve the efficiency of the proposed multi-period model, we incorporate a capacity sharing and cooperation mechanism whereby medical centers with low utilization rates share their under-utilized capacities to the other medical centers which are struggling to cope with the demand. The details of the capacity sharing algorithm are provided in Algorithm 1.

Based on the capacity sharing algorithm, first we identify all medical centers with demand higher than their capacity. Assume that medical center r is one of them. In the local transshipment network (i.e., $\eta_{rj} = 1, \quad \forall j \in \mathscr{D}$) of medical center r, the algorithm searches for all medical centers in that network where not more than 50% of their capacity is utilized. The capacity sharing mechanism is one of the main contributions of this study. The proposed percentage is simply an assumption used to determine whether a medical center is deemed to be under-utilized or over-utilized. Depending on if a medical center is considered over-utilized or under-utilized the sharing capacity mechanism might or might not be triggered. It remains at the discretion of the health care authority to determine the percentage based on circumstances they may face. The proposed model is capable of solving the problem using any other percentages. After identifying the under and over-utilized medical centers, the excess demand of the medical center r is randomly redistributed to these medical centers. The random selection process is a non-uniform random sampling where the probability of using a particular medical center for the capacity sharing with medical center r is computed based on the extent that its capacity is under-utilized.

4.1.3. Mobile units

In managing the emergency operations, as highlighted in the Literature Review section, using mobile units may assist to improve the supply network's efficiency. During a pandemic, any delay in vaccinating the entire population results in endangering public health as well as postponing the full recovery of the economy. Therefore, all methods which may expedite the vaccine administering process should be taken into consideration. We integrate a mobile unit network into the current multi-period allocation model to decrease the daily unmet demand and residual risk of unvaccinated population. We assume that m number of mobile units are available, each with C_m capacity. In each period, based on the demand and capacity of each medical center, the utilization rate is computed. Medical centers are sorted according to their capacity utilization rate and then mobile units are assigned to the m number of medical centers with the highest utilization rate. This dynamic capacity adjusting algorithm tries to improve the optimization model by alleviating the bottlenecks which are caused by the capacity constraints.

5. A case study: State of Victoria, Australia

Though scholars have researched various impacts of COVID-19 on the supply chain, most published articles are opinion-based and lack an empirical focus (Chowdhury et al., 2021). In this study, the proposed model for COVID-19 vaccine allocation is applied to the state of Victoria in order to evaluate the effectiveness of the model. Victoria is a state in the south-east of Australia with an estimated population of 7 million by 2022 (Australian Bureau of Statistics, 2020). The majority of Victoria's population concentrated in the central south part of the state, particularly the metropolitan region of Greater Melbourne. Melbourne has more than three-quarters of the Victorian population and is the second largest city in Australia. This study assumes that the target horizon of vaccinating the population by the Victorian government is approximately two months. The most updated information regarding the number and location of medical centers in the state has been extracted from the Department of Health, Victoria (Department of Health and Human Services, 2020). Fig. 4 shows the spatial distribution of 325 medical centers (i.e., demand points) in Victoria.

Algorithm 1: Augmented Multi-period Algorithm

Input: Input parameters are sets, parameters, and variables as listed in Table 3.

Input: d_{ij}

Output: d_{ij}^{upd}

  Initialization

    $c_1 \ldots c_6 \leftarrow 0$ initialize the counters.

    $d_i \leftarrow \emptyset$ initialize a vector of sum of demand medical centers with the size $i \in \mathscr{D}$ for all risk priority groups.

    $ur \leftarrow \emptyset$ initialize a vector of utilization rate of medical centers with the size $i \in \mathscr{D}$.

$d_i \leftarrow \sum_{j \in \mathscr{R}} d_{ij}, \quad \forall i \in \mathscr{D}$

$ur_i = \frac{d_i}{C_i}, \quad \forall i \in \mathscr{D}$

while $c_1 < i$ **do**

  if $d_i[c_1] > C_i[c_1]$ **then**

    $d_{ij}^{rem} \leftarrow \{\vec{0}\}$

    $C_i^{rem} \leftarrow C_i[c_1]$

    for $c_2 \leftarrow (j-1)$ **to** 0 **by** -1 **do**

      if $d_{ij}[c_1, c_2] < C_i^{rem}$ **then**

        $d_{ij}^{rem}[c_2] \leftarrow d_{ij}[c_1, c_2]$

        $C_i^{rem} \leftarrow C_i^{rem} - d_{ij}[c_1, c_2]$

      else

        $d_{ij}^{rem}[c_2] \leftarrow C_i^{rem}$

        $C_i^{rem} \leftarrow 0$

    $d_{ij}^{exss} \leftarrow \{\vec{0}\}$

    $d_{ij}^{exss} \leftarrow d_{ij}[c_1, :] - d_{ij}^{rem}$

    $c^{adj} \leftarrow \{Index(\eta_{ij}[c_1]) \mid \eta_{ij}[c_1] = 1\}[0]$

    $c_{<50}^{adj} \leftarrow \{c^{adj} \mid ur[c^{adj}] < 0.5\}$

    $ur^{adj} \leftarrow \{ur[c_3] \mid c_3 \in c_{<50}^{adj}\}$

    sort $c_{<50}^{adj}$ ascending based on the utilization rate

    $prob_{select} \leftarrow -1 \times Sort(-1 \times [\{\vec{1}\} - ur^{adj}])$

    $prob_{select} \leftarrow \frac{prob_{select}}{\sum prob_{select}}$

    while $\sum_{j \in \mathscr{R}} d_{ij}^{exss}! = 0$ & $len(c_{<50}^{adj})! = 0$ **do**

      $nbr \leftarrow Random.Choice(c_{<50}^{adj}, 1, prob = prob_{select})$

      while $\sum_{c_4 \in \mathscr{R}} d_{ij}[nbr, c_4] < C_i[nbr]$ & $\sum d_{ij}^{exss}! = 0$ **do**

        for $c_5 \leftarrow (j-1)$ **to** 0 **by** -1 **do**

          if $d_{ij}^{exss}[c_5]! = 0$ **then**

            $d_{ij}^{exss}[c_5] = d_{ij}^{exss}[c_5] - 1$

            $d_{ij}[c_1, c_5] = d_{ij}[c_1, c_5] - 1$

            $d_{ij}[nbr, c_5] = d_{ij}[nbr, c_5] + 1$

      $index_{del} \leftarrow \{Index(c_{<50}^{adj}) \mid c_{<50}^{adj} = nbr\}$

      update $c_{<50}^{adj} \leftarrow \{Del(c^{adj}[c_6]) \mid c_6 \in index_{del}\}$

      update $prob_{select} \leftarrow \{Del(prob_{select}[c_7]) \mid c_7 \in index_{del}\}$

      $prob_{select} \leftarrow \frac{prob_{select}}{\sum prob_{select}}$

  $c_1 = c_1 + 1$

$d_{ij}^{upd} \leftarrow d_{ij}$

return d_{ij}^{upd}

As explained in the Mathematical Model and Solution Approach section, by estimating the susceptibility rate of people during a pandemic, the risk clusters (priority groups) are defined. These clusters facilitate the process of assigning the eligible population into appropriate priority groups. Since forming the priority groups by using any multiple-criteria decision-making is a trivial task, in the current study we consider the age of applicants as a single criterion. Consequently, to estimate the susceptibility rate of Victoria's population, we use the number of deaths in each priority group and the population of the corresponding priority group. Therefore, the Victorian populace is categorized into five priority groups ($\mathscr{R}$) using the age as the clustering criterion. Fig. 5 depicts a comparison between the population of the state in 2021 (Australian Bureau of Statistics, 2020) and the number of
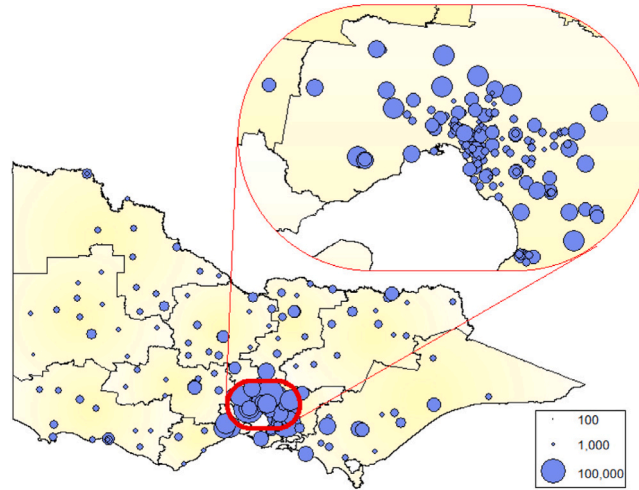
Fig. 4. Spatial distribution of the 325 medical centers in Victoria and their assigned demand.
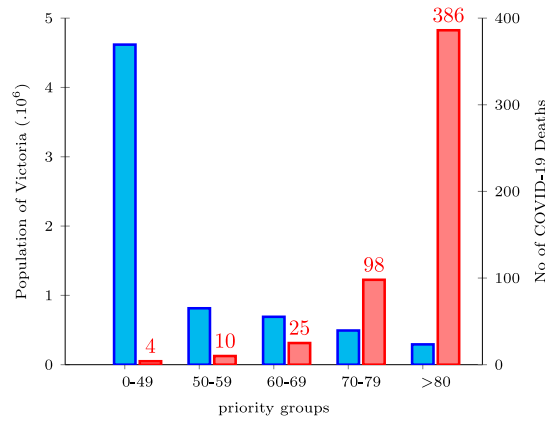

Fig. 5. Victoria's population and number of COVID-19-related deaths by priority group in 2021.

COVID-19-related deaths based on the priority groups until June 2021 in Victoria (Department of Health Australia, 2021) which indicates the susceptibility rate in each priority group.

In the next stage, the following parameters are determined: an estimation of the number of registered applicants to receive the vaccine (d_{ij}) in medical center $i \in \mathcal{D}$ for the priority group $j \in \mathcal{R}$; and also, the geospatial information of medical centers (Department of Health and Human Services, 2020) to estimate the travel time between medical centers (δ_{ij}). To estimate these parameters we use the Australian Statistical Geography Standard (ASGS) (Australian Bureau of Statistics, 2016). ASGS comprises the following main levels: Mesh Block (MB) which is designed as building blocks and as the smallest defined geographical area; Statistical Area Level 1 (SA_1) with the population of between 200 and 800 people; Statistical Area Level 2 (SA_2) which reflects functional areas as the representative of communities with both social and economic interactions together and with the population of between 3000 and 25,000 people; Statistical Area Level 3 (SA_3) which focuses on regional areas with similar regional characteristics, labor markets, and administrative boundaries, and with the population of between 30,000 and 130,000 people; Statistical Area Level 4 (SA_4) with a population above 100,000 persons; and finally, State and Territory (S/T), and Australia (AUS). Each level directly aggregates to its immediate higher level.

Note that the spatial distribution of the population of each priority group is determined based on the geospatial information of Mesh Blocks of Victoria (Barbieri and Jorm, 2019), Lat and Long of SA_2s, population of each SA_2 by priority groups (Victoria State Government Planning, 2019). To assign the population of SA_2s to medical centers as an estimation of demand, the following parameters are considered: set of SA_2s ($\mathscr{A}$), Lat and Long of MBs, Lat and Long of medical centers, and population of each SA_2 by age group, β_{ij} as the distance between the centroid of each SA_2 ($\forall j \in \mathscr{A}$) and each medical center ($\forall i \in \mathcal{D}$), and p_j as the total population of each SA_2 which is aggregated by age groups ($\forall j \in \mathscr{A}$). The outputs are θ_{ij}'s and β_{ij}'s.

This process includes two key sub-processes. In the first sub-process, to estimate ρ_j, first, Lats and Longs of centroid of SA_2s are obtained using the mean of Lats and Longs of MBs. Second, β_{ij} is estimated by measuring the travel time between the centroid of

each SA_2 and each medical center. Third, ρ_j is computed as the total population of each SA_2 which is aggregated from all priority groups located in the same area. In the second sub-process, the estimated ρ_j and β_{ij} are considered to be the inputs of an assignment model so that the values of θ_{ij} can be obtained. This determines the population of all SA_2s assigned to each medical center. The assignment model identifies the values of d_{ij} by summing the population of all SA_2s assigned to medical center i for each priority group j.

Details of the assignment model are as follows: the total travel time between SA_2s and medical centers is minimized in the objective function (Eq. (5.1)); Constraints 5.2 ensure that only one medical center is assigned to each SA_2; Constraints 5.3 state that at least one SA_2 should be assigned to a medical center; and Constraints 5.4 impede assigning of only one SA_2 with zero population to a medical center.

The final step is to randomly distribute the demand (d_{ij}) for a vaccine over the planning horizon of 60 days. We use Dirichlet distribution to randomly generate 60 weights between 0 and 1 given that the sum of these weights is equal to 1. It is expected that the likelihood of having more bookings at the earlier stages of the planning horizon is higher than the later stages of administering period. Hence, multiplying 60 Dirichlet random values which are sorted in descending order by d_{ij} results the daily number of unvaccinated people in risk cluster $j \in \mathcal{R}$ who registered to receive the vaccine in medical center $i \in \mathcal{D}$.

$$\min \sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{A}} \beta_{ij} \theta_{ij} \tag{5.1}$$

$$S.t:$$

$$\sum_{i \in \mathcal{D}} \theta_{ij} = 1, \quad \forall j \in \mathcal{A} \tag{5.2}$$

$$\sum_{j \in \mathcal{A}} \theta_{ij} \geq 1, \quad \forall i \in \mathcal{D} \tag{5.3}$$

$$\sum_{j \in \mathcal{A}} \theta_{ij} \rho_j \geq 1, \quad \forall i \in \mathcal{D} \tag{5.4}$$

$$\theta_{ij} \in \{0, 1\}, \quad \forall i \in \mathcal{D}, \quad \forall j \in \mathcal{A} \tag{5.5}$$

To compare results of this study in terms of risk of unvaccinated population with the single-period allocation model (Abbasi et al., 2020), the following identical settings are employed:

Since state of Victoria serves as the case study, identical sets of medical centers ($\mathcal{D}$) and priority groups ($\mathcal{R}$) are considered. Similarly, d_{ij} as the total demand for unvaccinated people in priority group $j \in \mathcal{R}$ who are booked to receive the vaccine in medical center $i \in \mathcal{D}$ is estimated using the method explained earlier. Moreover, by having the Lat and Long of each medical center extracted from the Geo-location API of the Google Cloud platform (Department of Health and Human Services, 2020), duration of travel time between each pair of medical centers (δ_{ij}) is estimated for Victoria. With respect to M as a big number, considering the values of other parameters, value of 10^5 is selected.

Within the local transshipment network of any particular medical center, the maximum number of medical centers in its vicinity that can transship the vaccines is considered to be $m = 10$. Planning horizon is also set to be 60 days.

The daily capacity of medical centers (C_i) for administering the vaccines can significantly vary according to the resources each medical center has available. Furthermore, proportionate to the total population of SA_2s assigned to each medical center, a state-level government can readily expand the capacity of a medical center for administering more vaccines per each period. Therefore, since the capacity of a medical center for administering the vaccine during a pandemic can be very flexible, using random values seems to be reasonable. However, to generate random numbers which mimic a pandemic's situation, given that the average demand of medical center i for each day of planning horizon is $\frac{\sum_{j \in \mathcal{R}} d_{ij}}{60}$, we consider Uniform random values with the lower limit of $\frac{0.8}{60} \sum_{j \in \mathcal{R}} d_{ij}$ and upper limit of $\frac{1.2}{60} \sum_{j \in \mathcal{R}} d_{ij}$ for C_i.

To estimate the weight of priority groups (λ_j), the quotient for the number of COVID-19-related deaths in Victoria and the population of the state (refer to Fig. 5) is obtained for each age group and then results are normalized to 100%. The estimated weights of priority groups for five age groups of 0–49, 50–59, 60–69, 70–79, and above 80 are $\lambda_j = \{0.00053243, 0.00728099, 0.02144653, 0.12265288, 0.84808718\}$, respectively. Next, γ as the minimum difference between the weights of each pair of priority groups is estimated.

The common penalty coefficient for the transshipment and vaccine returns is set to be $\epsilon = 6e - 8$. This parameter is required to ensure that the transshipment mechanism is triggered only when there is no further opportunity to allocate vaccines directly from the DC. The value of ϵ depends on the pack size (P). As Abbasi et al. (2020) stated, it means the demand point needs to return $P - 1$ units to DC, given that P is greater than 1. The value of ϵ is selected in a way that the condition ($\epsilon \leq \frac{min(\lambda_j)}{\delta(P-1)}$ where $\delta = max(\delta_{ij})$) is satisfied. $P = 1$ indicates that no transshipment is required. Sending a vaccine pack to a demand point that needs only one vaccine unit and there is not any transshipment possibility to other medical centers is obviously better than keeping the vaccine pack in the DC.

Capacity of transshipment network is also estimated as $\mathcal{K} = \lfloor \frac{i}{3} \times 5 \times 60 \rfloor = 32{,}499$ minutes. This estimation is undertaken considering that here are 325 medical centers in the state of Victoria and we assumed that each vehicle with 5 operating hours a day can transship the vaccines among 3 demand points. It means for every 3 medical centers we can allocate one vehicle.

To estimate the daily available vaccine packs in DC, the following formula is used: $Q = \lfloor \frac{\sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{R}} d_{ij}}{\text{planning horizon} \times P} \rfloor = 9{,}597$ packs. Note that the total population of the state is equal to the total demand intending to be vaccinated during the planning horizon. Moreover, each pack of vaccine contains P number of vaccine units.
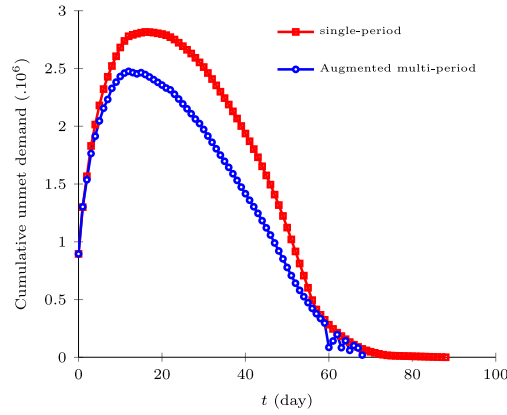
Fig. 6. Cumulative unmet demand.

To solve the proposed multi-period model in this study, a computer with the following specifications is utilized: 64 GB RAM and Intel Xeon CPU E5-2680 V3 @2.5 GHz. The multi-period window is also considered as $MPW = 14$ which reflects our maximum computational power to solve the model in a reasonable amount of time. The model is implemented in Python version 3.8.0. Moreover, for the optimization process CPLEX 20.1 optimizer is used. Additionally, the relative MIP gap tolerance is set to 1e-4 to command CPLEX to stop the optimization process as soon as a feasible integer solution is identified. The following sections describe the results of the multi-period vaccine allocation model.

5.1. Cumulative unmet demand

The cumulative unmet demand for period t is an indication of $\sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{R}} d_{ij}^t + \sum_{\tau=1}^{t-1} \sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{R}} (d_{ij}^\tau - x_{ij}^\tau)$ where for each period, the accumulated unmet demand of all previous periods ($\sum_{\tau=1}^{t-1} \sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{R}} (d_{ij}^\tau - x_{ij}^\tau)$) is added to the demand of the current period. According to the settings of this experiment, $\sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{R}} d_{ij}^t$ is a decreasing function in period t as demand for receiving vaccines is higher than available supply at the earlier stages of the planning horizon. This is due to the fact that most people are willing to receive the vaccine as soon as possible. Given that there is a cap on the available vaccine supply, the cumulative unmet demand reveals an increasing trend at the beginning of the administering horizon until a turning point is reached where supply catches up the demand.

Fig. 6 compares the cumulative unmet demand of the single-period and the augmented multi-period allocation models given that the planning horizon is considered to be 60 days. Results indicate that: (i) the rate of deduction in cumulative unmet demand for the augmented multi-period model is higher than the single-period counterpart; and (ii) length of administering horizon for the single-period model is significantly greater than the augmented multi-period model. In other words, using the multi-period model leads to vaccinating the Victorian population in 69 days (surplus = 9 days) while employing the single-period model results in an extended administering horizon to 90 days (surplus = 30 days).

The main reasons behind such a significant improvement are three-fold. First, allocation decisions are made over multiple period in the augmented multi-period model which outperforms the sub-optimal decisions of the single-period allocation model. Second, unlike the single-period model, the improved inventory policy of the DC in the proposed multi-period allocation model provides an opportunity to use the oversupplied vaccine units to achieve more effective resource utilization rather than ignoring them in the next period. Third, at the end of the administering period where the system experiences an unbalanced utilization rate for medical centers, capacity sharing mechanism boosts the operational efficiency of the augmented multi-period model.

During a pandemic, governments try to strike a balance between saving the lives and livelihoods of the population using all available resources. In Australia, the federal government has decided to open the national borders once the majority of the population is vaccinated. It is undeniable that the bulk of economic growth depends on easing the country and state-level restrictions as well as lifting the border closures throughout the country. The shortened administering horizon and decreasing the number of unvaccinated people provide an opportunity to save more lives and/or the livelihoods of the population in the most effective manner.

5.2. Residual risk

In this study, the residual risk is computed by $\sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{R}} (\lambda_j + \gamma \frac{d_{ij}'^t}{\sum_{l \in \mathcal{D}} d_{lj}'^t})(d_{ij}'^t - x_{ij}^t)$ which is the first component of the objective function for a particular period. In this formula, $d_{ij}'^t$ is the demand of current period and the cumulative unmet demand of all previous periods ($\sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{R}} d_{ij}^t + \sum_{\tau=1}^{t-1} \sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{R}} (d_{ij}^\tau - x_{ij}^\tau)$). Residual risk is a pivotal factor which indicates the weighted risk of the people in each period who have not yet been vaccinated. To estimate the weighted risk of the unvaccinated population, susceptibility rate and exposure risk are incorporated into the measurement system. Fig. 7 illustrates a comparison between the
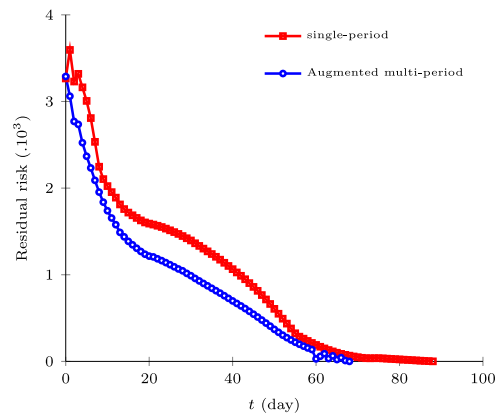
Fig. 7. Residual risk.

residual risk of the augmented multi-period model and the single-period counterpart for the state of Victoria. Results show that the residual risk using the augmented multi-period allocation model is significantly lower than the results of the single-period model throughout the administering horizon. Further, similar to the cumulative unmet demand, the augmented multi-period model provides a superior performance in terms of vaccinating the whole population in a shorter period of time.

Consequently, it can be observed that the capacity sharing, cooperation among medical centers, making the allocation decisions over multiple periods, and employing an improved inventory policy for the DC all play significant roles in achieving superior results in terms of minimizing the residual risk and vaccinating people more quickly. Note that lower residual risk of the unvaccinated population provides various benefits to not only individual citizens but also to the whole population in terms of controlling community transmission. It is also obvious that although minimizing the cumulative unmet demand is crucial for a country/state, the major health-related consequences of a pandemic (e.g., death rate) are closely dependent on the residual risk of the unvaccinated population. Decreasing the residual risk as well as diminishing the cumulative unmet demand are concurrent benefits that a government may achieve through employing the proposed augmented multi-period allocation model.

5.3. Transshipment

Transshipment is one of the mechanisms which can improve the operational efficiency of a distribution network particularly when the capacity of a service provider is limited in a supply network's nodes. In the proposed allocation model, given that vaccines are distributed in packs, any mismatch between the exact value of demand in a medical center and the number of units that it receives from the DC can be eased by using the transshipment mechanism. Doing so results in further reduction in the residual risk of the unvaccinated population.

As explained earlier, the residual risk of unvaccinated people is closely linked to the death rate resulting from a pandemic. There is no doubt that all mechanisms which may be effective to reduce the residual risk should be incorporated into the allocation model. It is also undeniable that when vaccines are distributed in packs, since there is no guarantee that the demand of a medical center in a period would be divisible to the number of receiving packs, it is quite likely that some medical centers would be in an over-supply position while others experience shortages. Consequently, when direct allocation of vaccines from the DC is not available in a period, if an allocation model can boost the transshipment mechanism in a network, the unmet demand of unvaccinated people can be further reduced. In addition, transshipment mechanism can provide an opportunity to decrease the residual risk by shipping the vaccine units from a demand point with less risky cases to the medical center(s) in which people belonging to the high-risk priority groups wait to be vaccinated.

Fig. 8 presents a comparison between the total number of transshipments among the medical centers for the single-period and augmented multi-period allocation models. It can be observed that the total number of transshipped vaccine units using the augmented multi-period model is significantly higher than the single-period allocation model. This is one of the key reasons behind the further decline in the residual risk which was discussed in the previous section.

To understand why the transshipment mechanism provides a superior performance in the augmented multi-period model, a couple of technical factors should be considered. First, identifying the transshipment opportunity in a single-period model is linked to the over and under-supplied demand nodes as well as prioritizing high-risk groups for a single period only. In contrast, when allocation and transshipment decisions are made concurrently for multiple periods, it is more possible to identify further opportunities to reduce the residual risk by employing the transshipment mechanism. Second, direct allocation of vaccine units from the DC can be adjusted by incorporating the transshipment mechanism. Assume that a demand point needs 100 units, the pack size is 12, and the capacity of a medical center is higher than demand. It is obvious that DC may consider dispatching either 8 or 9 packs to this demand point. However, one of these decisions provides the least residual risk. Focusing only on a single period may undermine the opportunity of further transshipment in the network. Third, returning the vaccine units to the DC is an inevitable
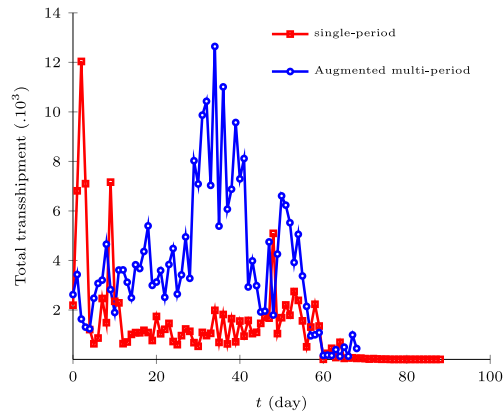
Fig. 8. Transshipment of vaccines among medical centers.

but undesired mechanism in the allocation model. The number of transshipped units is higher in the augmented multi-period model since it is more likely to identify a transshipment opportunity than returning the vaccines to the DC when allocation decisions are made over multiple periods.

It is necessary to highlight that the designed return process is a complementary mechanism which is not desirable, in particular for the single-period model that is proposed in the aforementioned article. One of the merits of the developed multi-period model is that the number of returned vaccines to the DC can be used in the subsequent periods to further minimize the risk posed by the unvaccinated population, whereas if a base-stock policy is considered for the single-period model, the returned items are lost. Based on coefficients of the three components of objective function, since cost of returning a vaccine unit is higher than transshipment, and cost of transshipment is higher than using a vaccine unit in the medical center which actually receives the vaccine pack, the chance of returning the vaccine unit to the DC is very low. Note that for the developed vaccine allocation model, cost does not refer to the monetary value and it is the penalty that is formulated to prioritize the three components of objective function. To understand the likelihood of returns, we have measured the total number of returns over the administering horizon. Results show that in total 113,559 vaccine units were returned to the DC over the administering horizon. It confirms that a very small proportion (1.6%) of the total allocated vaccine units have been returned to the DC.

5.4. Multi-period window (MPW)

In the previous sections, the logic behind developing a multi-period allocation model has been discussed. There is a limitation in computational power to design and implement a multi-period model. Due to this restriction, the MPW is selected as 14 which reflects the maximum time window that our computational power is able to solve the proposed multi-period allocation model. However, given that emergency response units may not have access to our hardware, it is crucial to understand that if less computational power is available (i.e., lower MPW), how the optimal solution is impacted.

Fig. 9(a) illustrates the total cumulative unmet demand for MPW of 6, 10, and 14 days. Moreover, Fig. 9(b) represents the total residual risk for the same MPWs. The results show that by decreasing the MPW, the output of the allocation model in terms of both total cumulative unmet demand and total residual risk is aggravated. For this reason, it is essential for the emergency response planning units to use the most powerful computational power in hand to deliver the most effective allocation of vaccines to the medical centers. Note that although increasing the MPW results in an improved optimal solution, the computational time required for solving the model also increases. The trade-off between using the higher MPW and maximum reasonable computational time should also be considered by decision-making units.

5.5. Mobile units

Various capacity constraints are involved when making decisions about allocation. In the proposed model, the daily available vaccine packs in the DC, capacity of medical centers, and transshipment network are taken into account. Although both vaccine supply and capacity of medical centers are exogenous variables to the allocation model, there is an opportunity to incorporate an augmenting mechanism to alleviate the restrictions regarding the capacity of the medical centers.

Basically, a state-level government can consider the option of employing a number of mobile units in the vaccine administering process during a pandemic. These mobile units can enhance the operational efficiency of the allocation model by providing extra and flexible administering capacity. To explore how well this opportunity improves matters, we incorporate a mobile unit network in which each unit has an administering capacity of 500 vaccines per day.

Fig. 10(a) shows the cumulative unmet demand with and without engaging 10 mobile units to provide assistance to medical centers with the highest utilization rate in each period. In this analysis, the multi-period window is considered as 14 days. It can
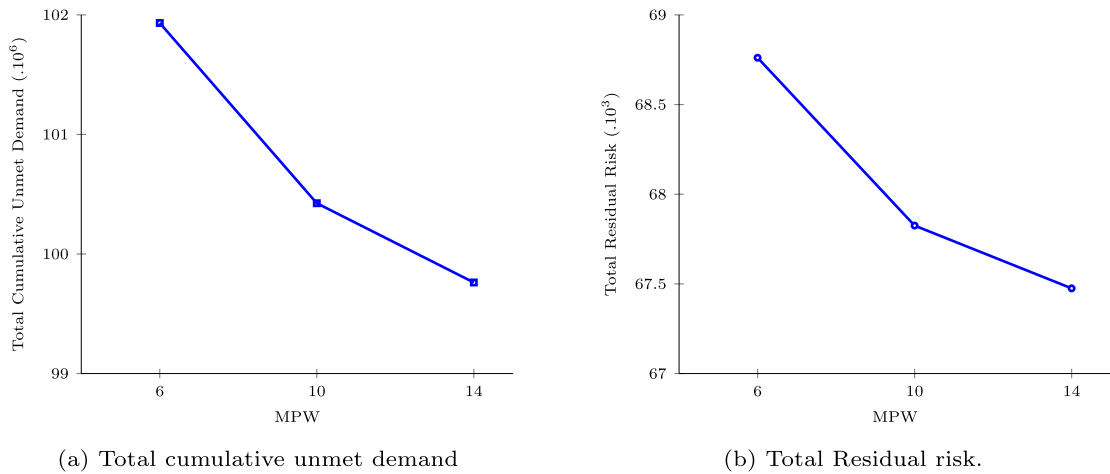
(a) Total cumulative unmet demand

(b) Total Residual risk.

Fig. 9. Comparing the cumulative unmet demand and residual risk for multi-period windows of 6, 10, and 14 days.

(a) Cumulative unmet demand
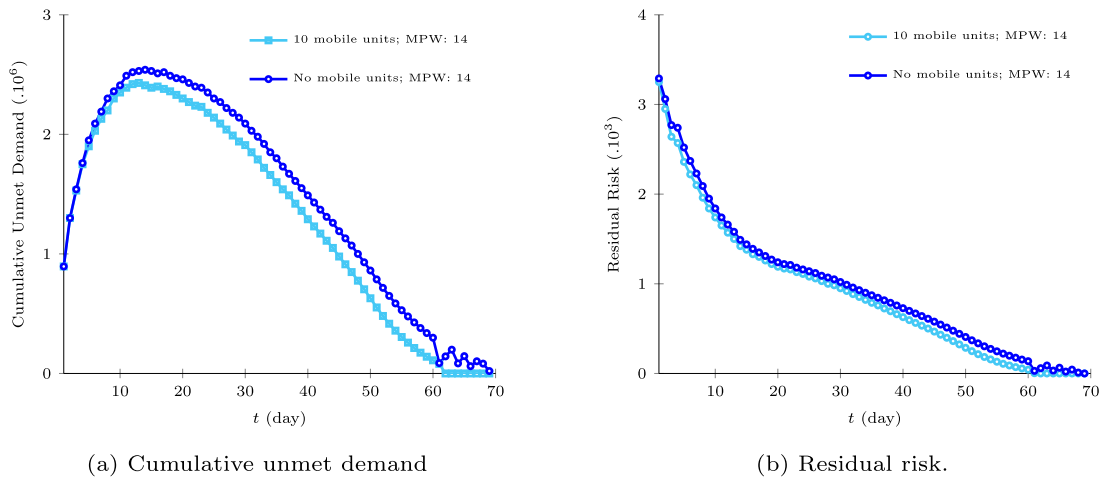
(b) Residual risk.

Fig. 10. Comparing the cumulative unmet demand and residual risk for administering network with and without mobile units.

be observed that incorporating mobile units leads to a decline in the cumulative unmet demand after the first ten days of the administering horizon. The reason for the ineffectiveness of mobile units in the earlier stage of the administering process is that: firstly, during this stage vaccine supply is significantly less than the demand; and secondly, the capacity of medical centers is not binding. In other words, extra capacity of mobile units would be redundant when the supply chain suffers from vaccine shortages. Later, when a sufficient number of vaccine units are available, capacity constraints of over-utilized medical centers can be alleviated by employing the mobile units.

In addition to reducing the cumulative unmet demand, Fig. 10(b) highlights an improvement in diminishing the residual risk of unvaccinated people when mobile units are employed. Note that engaging mobile units provides two benefits to the allocation model: (i) the total capacity of administering process increases; and (ii) since this extra capacity is flexible and can be assigned to the medical centers with the highest utilization rate, the marginal benefit of increasing one unit of capacity through mobile units is higher than increasing the same amount of capacity to the current medical centers.

To further investigate the efficiency of using mobile units, another experiment is designed in which 20 mobile units are employed where MPW is 10 days. To understand the reason behind designing this experiment, suppose the emergency response unit of the state does have access to a top-of-the-range hardware with high computational power. The question here is when the computational power is moderate (MPW=10), would adding more mobile units (20) be able to make up for the inefficiencies resulting from using the multi-period model with moderate MPW (lower computational power)? Figs. 11(a) and 11(b) confirm what we have observed in the previous experiment as using a dynamic capacity adjusting algorithm (i.e., adding mobile units) is able to improve the optimization model. It does this by alleviating the bottlenecks caused by the capacity constraints of medical centers. Moreover, in the case of having less computational power, adding more mobile units may be deemed a complementary strategy to hit a set target regarding the rate of deduction in the cumulative unmet demand and/or the residual risk of the unvaccinated population.
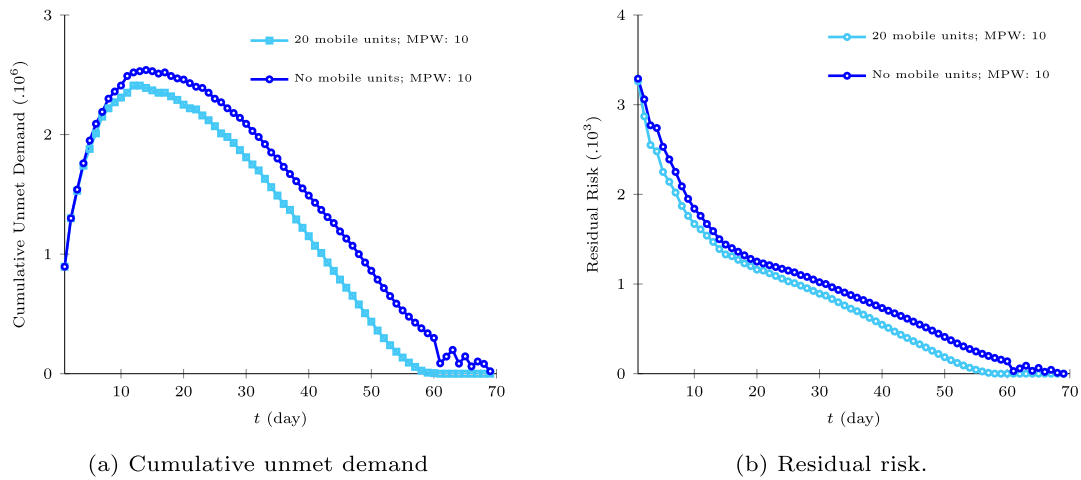
(a) Cumulative unmet demand

(b) Residual risk.

Fig. 11. Comparing the cumulative unmet demand and residual risk for administering network with and without mobile units.

Table 4
Comparing administering period, solving time, and total residual risk for various problem sizes with/without employing the mobile units.

Size	Augmented mechanism	Administering period	Sol. time (hh:mm)	Total residual risk
$i = 325,\ Pop = 6,861,925,\ Q = 9,597$	1	69	02:08	6.75E4
$i = 200,\ Pop = 4,647,940,\ Q = 6,455$	1	69	01:32	4.53E4
$i = 100,\ Pop = 2,430,979,\ Q = 3,376$	1	67	01:06	2.47E4
$i = 325,\ Pop = 6,861,925,\ Q = 9,597$	1, 2	61	01:52	6.16E4

1: Capacity sharing mechanism.
2: Mobile units.

5.6. Solving time

To investigate how size of the problem may impact the solving time and key operational outputs, three problem sizes are created: small (population = 2,430,979), medium (population = 4,647,940), and large (population = 6,861,925). These states have 100, 200, and 325 medical centers, respectively. Proportionate to the population, the daily available packs of vaccine for small, medium, and large states are estimated to be 3376, 6455, and 9597, respectively. To make a fair comparison, all other parameters are the same in these experiments. Note that the travel time between the medical centers and their respective capacities are selected from the original experiment for the medical centers.

Results show that the solving times are 01:06, 01:32, and 02:08 for small, medium, and large problems, respectively (Table 4). Confirmed here is that the solving time is in a reasonable range to provides an opportunity for the emergency units to plan for vaccine allocations prior to the administering period. Note that since the proposed solution approach breaks down the administering period into shorter periods, any problem size can be addressed using the developed method. To compare the results, the total residual risk which is the sum of residual risk of all days over the administering horizon (the area under the curve of the residual risk) and the length of administering period are considered. As expected, the total residual risk and the length of administering period are lower for smaller problem sizes. Furthermore, it can be observed that employing mobile units for the original problem size leads to lower total residual risk (6.16E4) and a shorter administering period (61 days). (See Table 4.)

6. Discussion and policy implications

Global pandemics such as COVID-19 show that the key solution to overcoming the challenges of immunizing the population is to build quick emergency response and the fastest possible vaccination process according to the (National Governors Association Center for Best Practices, 2020). DHL (2020) asserts there are critical challenges that governments face with respect to medical supplies during a pandemic such as demand identification and forecasting, sourcing, procurement, inbound logistics, allocation, and distribution. In this regard, vaccine allocation has been identified as one of the most critical stages in an emergency response plan especially for countries with several levels of government (e.g., federal, state and local), such as Australia (DHL, 2020). This matter along with the severe impacts of the COVID-19 pandemic has motivated us to develop an effective vaccine allocation model in order to minimize the risk of unvaccinated population within the shortest possible administering period. Since the ultimate aim of a vaccine allocation decision support system is to effectively allocate vaccines in such a way that the risk of severity and fatality

of a pandemic is minimized, in the proposed model the susceptibility rate and exposure risk factors are encapsulated to prioritize the most vulnerable people in the community.

Recently, a vaccine allocation model is suggested by Abbasi et al. (2020) for the COVID-19 pandemic. We have improved their study by proposing a multi-period vaccine allocation model along with several complementary mechanisms including capacity sharing, cooperation and employing mobile units to further minimize the risk posed by the unvaccinated population and shorten the administering horizon.

From the theoretical perspective, the most accurate vaccine allocation model should consider the entire length of the planned administering horizon for making the right allocation decisions. For example, if the Victoria's government plans to vaccinate the population in 60 days, a multi-period allocation model with a window of 60 can be the most effective. As a theoretical contribution, we have designed a multi-period allocation model which works with any time window. However, the practical challenge is that depending on the available computational power, the model can be solved for a limited number of periods in a reasonable amount of time. This challenge led us to develop an innovate algorithm to solve the multi-period model for any number of periods that the available computational power could cope with, and then systematically transferring the results to the subsequent allocation decisions for the entire length of the administering horizon. The finalized algorithm is the key contribution of this study to solution methodology whereby a multi-period vaccine allocation model can be solved using any computational power. We have shown that using higher computational power (i.e., the allocation model with more concurrent allocation decisions) will produce more accurate results.

A review of the literature shows how transshipment is able to improve the efficiency of a distribution network (Dennis et al., 2011). Although the direct benefit of a multi-period model is to make allocation decisions over multiple periods, as a theoretical contribution, we have shown that the level of transshipment is boosted when a multi-period allocation model in employed. This is particularly crucial for the vaccine allocation model as vaccines are distributed in packs with a specific pack size. Therefore, emergency planning units are recommended to use both the multi-period vaccine allocation model and transshipment mechanism in their decision support system. Similarly, capacity sharing and cooperation mechanism have been widely used to improve a distribution network's efficiency (Seok and Nof, 2014). Nonetheless, it is crucial to understand how this complementary mechanism can be used in the vaccine allocation model. Our analysis showed that at roughly the second half of the administering horizon, some medical centers were in the over-utilized position whereas others employed less than fifty percent of their capacity. These imbalanced utilization rates definitely result in undesirable outcomes such as longer administering horizon and greater risk of having an unvaccinated population. So, to boost the operational efficiency of the allocation model, we have embedded a capacity sharing mechanism which dynamically reduces the difference between the highest over-utilized demand nodes and the lowest under-utilized medical centers. The practical implication of empowering the allocation model with the capacity sharing mechanism is that; firstly, the capacity of all service providers (i.e., medical centers) are used in the most efficient way; and secondly, the emergency response units would be able to meet the target administering horizon with higher probability. It is obvious that our proposed mechanism also results in immunizing the population faster which in turn leads to various health-related and economic benefits.

We have also investigated how the Australian government distributes vaccine packs. A specific number of vaccine packs is allocated from the federal government to the states and territories based on their population. It is safe to assume that the inventory of distribution center for each state is replenished to a certain level on a regular basis. Given that a number of vaccine units are returned to the DC in each period, we have amended the single-period model whereby in our proposed model the returned vaccines are added to the replenished stock of the next period. This contribution significantly improves the performance of our vaccine allocation model since the returned vaccines may be actually allocated in the subsequent period.

During a pandemic, it is expected that governments and health authorities marshal all available resources to expedite the vaccine administering process and enhance its efficiency. The bottlenecks, however, may perform a hidden role of restricting the vaccine administering process. One key impediment in the vaccine allocation process is the capacity of medical centers to administer the vaccines. From a practical angle, increasing the current capacity of a medical center is challenging. Further, it is not an easy task to predict which medical center will be over-utilized in each period. Therefore, a flexible supporting capacity is required which can be transferred between the medical centers in each period. To overcome this challenge, we have developed a mobile unit network as an ameliorating mechanism to further boost the operational efficiency of the administering network. The results of our analysis confirmed that using such a network would help to significantly decrease the cumulative unmet demand and residual risk of the unvaccinated population. The managerial implication of this finding is that when bottlenecks in the administering process are identified to be the capacity of medical centers, emergency response planning units may consider employing a mobile unit network to improve the whole vaccination process.

From the theoretical perspective, the proposed multi-period model can effectively allocate the vaccine packs during a pandemic. Moreover, we have shown that using a higher time window results in the model performing better. The developed algorithm provides an opportunity to use the multi-period model when the available computational power is limited and solving the model for the entire length of planning horizon is not feasible. However, from a practical viewpoint, it is worth clarifying whether using the mobile unit network can make up for the inefficiencies that are resulting from low to moderate levels of computational power. Although it is not a feature-for-feature comparison, the results provide a recommendation to emergency planning decision-makers as the mobile unit network is capable of covering some parts, if not all, of the sub-optimal allocation decisions which are made when the multi-period model is solved for lower length MPW. This recommendation is more effective when the key bottleneck in the administering process is linked to the capacity of medical centers.

6.1. Managerial implications

In this section, we summarize the benefits that emergency response units and logistics operations managers can reap from the results of this study. Firstly, it is obvious that during a pandemic, shortening the administering period length and achieving the least possible risk of an unvaccinated population are the key targets of all government-level and state-level authorities given the associated health and economic advantages. The developed multi-period model can help achieve these goals as allocation, transshipment, and return decisions are made over multiple periods. Secondly, the designed solution approach whereby a multi-period vaccine allocation model can be solved using any computational power further improves the effectiveness of the proposed decision support system, and it can be easily embedded into any online platform for allocation decision processes. Thirdly, flexibility is a key success factor for a vaccine allocation model as emergency response units may encounter various unforeseen circumstances. The designed capacity sharing mechanism and incorporating the mobile units into the administering fleet not only results in shrinking the length of the administering period, but they also provide powerful tools for logistics operations managers to make fine-tuned adjustments to achieve the highest possible efficiency from the distribution and administering networks. Fourthly, the proposed vaccine allocation model enables the returned vaccine units to be used in subsequent periods which is vital to maximize the vaccination rate as one of the key objectives of logistics operations managers. It is worth highlighting that the above-mentioned managerial implications are not limited to the COVID-19 pandemic and logistics operations managers. Emergency response planning decision-makers can also reap the benefits of the proposed model during any global pandemic.

7. Conclusions and future research

In any pandemic outbreak, health authorities strive to administer a vaccination to the whole population within the shortest possible time in order to contain the spread of the virus. To achieve this goal, many research studies have attempted to design an effective and efficient vaccine supply chain. Reviewing the extant literature reveals that a significant number of studies have tried to separately explore the allocation and distribution components of the vaccine supply chain. We showed that combining these two components into a comprehensive model can effectively mitigate the risk involved in such pandemics. The main objective of the proposed vaccine allocation model in this study is to effectively distribute and allocate the vaccines among demand points, whereby the vulnerable people with high susceptibility rates are given high priority. Moreover, to minimize community transmission of the virus, the proposed vaccine allocation model can give higher priority to those who are residing in geographical areas with higher population densities which would ultimately result in mitigating the exposure risk.

The proposed vaccine allocation process starts with an estimation of the population in the catchment area of each demand point. Then, those who are willing to be vaccinated will register via an online booking system. Based on the data collected through this system, the susceptibility rate of the applicants will be computed for each priority group. Categorization of priority groups forms the first input to the allocation decision stage. The second input is the estimate of the exposure risk which is defined as the probability of the disease transmission within a community. The available vaccine pack distributed to DCs along with the size of vaccine pack are the next inputs to the allocation decision stage. The proposed model will allocate the vaccine to the medical centers taking into account transshipment and return mechanisms. Due to uncertainties surrounding the allocation decisions, the medical centers might be over or under-supplied. Therefore, the vaccine transshipment between medical centers is considered in the proposed model to effectively meet the need of all medical centers. Using the above inputs and applying a mathematical model, the vaccine allocation model is capable of concurrently optimize direct vaccine allocation from DC, indirect vaccine allocation through transshipment, and the mechanisms to return unused vaccine to the DC, which ultimately result in minimizing the risk of unvaccinated population in the shortest administration horizon.

The augmented multi-period vaccine allocation model proposed in this study would yield the following results. Firstly, by employing this model, the cumulative unmet demand during the target horizon is always lower compared to a single period model. Having less cumulative unmet demand results in lower residual risk of unvaccinated people which decreases the risk of community transmission of the virus. Secondly, employing the proposed model shortens the length of the vaccination administering horizon. This is mainly due to employing the capacity sharing and cooperation as a complementary mechanism which provides the opportunity to redistribute the oversupplied vaccines among eligible medical centers. It does this by considering the total available travel time for vehicles to facilitate the transshipment of vaccines among those medical centers. In fact, the proposed vaccine allocation model allows the emergency response planning units to redistribute the oversupplied vaccines and achieve more effective resource utilization. Furthermore, this study incorporates mobile units to the multi-period vaccine allocation model which provides additional support to medical centers with high utilization rate in each period. Mobile units also provide extra and flexible capacity to the vaccination system which remarkably enhances the operational efficiency of the proposed allocation model. Consequently, using mobile units enable the governments to lessen the bottlenecks caused by the capacity limitations during the vaccination administrating horizon. In summary, this study provides both theoretical contributions and practical implications which facilitate the decision makers in incorporating logistics aspects of vaccine allocation mechanisms and to manage the administering efforts to be more effective and productive in the overall vaccine allocation process.

Our proposed model shows the important role of transshipment mechanism in achieving a more effective and efficient vaccine supply chain. While almost all of the research focus on direct vaccine allocation from a distribution center, we explained the significant role that indirect allocation can play in vaccine supply chain. Such indirect vaccine allocation is possible through incorporating transshipment mechanisms in the proposed model. As a result, our research showed that the unmet demand of the unvaccinated population can be further reduced through the inclusion of the transshipment mechanisms in which the utilization

of excess vaccine is maximized. Our findings in this research agreed with Choi (2021) who posits that the risk involved in COVID-19 can be better managed using a multi-period planning approach. Our proposed model shows a reduced risk of unvaccinated population compared to a single-period model proposed by Abbasi et al. (2020). Our proposed model is applicable in other contexts. In any pandemic allocation problems, the main aim is to inoculate people as soon as possible to curb the destructive impacts of the pandemic. Researchers consider other objectives such as cost, equity or total number of infections. There is no doubt the input parameters would differ in other contexts depending on many variables such as demand, vaccine supply, available resources such as number of mobile units, the number and capacity of medical centers, etc.

In general, the distribution problem in the vaccine supply chain can be viewed under pandemic or non-pandemic circumstances. such scenarios will have a direct impact on the structure of the objective function. When there is no outbreak of a new disease (non-pandemic situation), the objective function is formulated to minimize the total vaccine supply chain cost including fixed costs (e.g., new administering centers) and/or variable costs (e.g., transporting the vaccine units). Conversely, in a pandemic situation when the lives of people are at stake and all economic factors are linked to vaccinating the populace at early as possible, the objective function is formulated to minimize the risk of having an unvaccinated population. For example, Yang and Rajgopal (2021) proposed a multi-period allocation model within the context of a non-pandemic vaccine supply chain. They use an approach known as outreach to increase the immunization rates among geographically dispersed and nomadic populations in low- and middle-income countries. The proposed allocation model in their study is revised for each period based on the changes in population and the travel time between locations. This is based on the premise that the population might change due to reasons like seasonal migrations or changes in travel time because of natural disaster. In comparison, in the current study, a vaccine supply network is designed to tackle a pandemic. The allocation model is revised for each period based on the vaccine demand in the current and future periods. Due to the novelties in the approach and the context of our study, there are some limitations which can be further investigated in future research.

CRediT authorship contribution statement

Masih Fadaki: Conceptualization, Modeling, Analysis, Writing – original draft, Review & editing. **Ahmad Abareshi:** Conceptualization, Writing, Introduction, Literature Review, Operationalization, Review & editing. **Shaghayegh Maleki Far:** Conceptualization, Writing, Analysis, Discussion, Conclusion. **Paul Tae-Woo Lee:** Writing structure, Policy implications, Review and feedback.

References

Aaby, K., Herrmann, J.W., Jordan, C.S., Treadwell, M., Wood, K., 2006. Montgomery county's public health service uses operations research to plan emergency mass dispensing and vaccination clinics. Interfaces 36 (6), 569–579.

Abbasi, B., Fadaki, M., Kokshagina, O., Saeed, N., Chhetri, P., 2020. Modeling vaccine allocations in the COVID-19 pandemic: A case study in Australia. Available at SSRN 3744520.

Ali, I., Alharbi, O.M., 2020. COVID-19: Disease, management, treatment, and social impact. Sci. Total Environ. 728, 138861.

Araz, O.M., Galvani, A., Meyers, L.A., 2012. Geographic prioritization of distributing pandemic influenza vaccines. Health Care Manag. Sci. 15 (3), 175–187.

Arifoğlu, K., Tang, C.S., 2021. A two-sided incentive program for coordinating the influenza vaccine supply chain. Manuf. Serv. Oper. Manag..

Assi, T.M., Brown, S.T., Kone, S., Norman, B.A., Djibo, A., Connor, D.L., Wateska, A.R., Rajgopal, J., Slayton, R.B., Lee, B.Y., 2013. Removing the regional level from the niger vaccine supply chain. Vaccine 31 (26), 2828–2834.

Australian Bureau of Statistics, 2016. Australian statistical geography standard. https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/bySubject/1270.0.55.001{~}July2016{~}MainFeatures{~}Mainstructure{~}10002. (Accessed December 2021).

Australian Bureau of Statistics, 2020. Population projections, Australia. URL https://www.abs.gov.au/statistics/people/population/population-projections-australia/latest-release. (Accessed December 2021).

Azadi, Z., Gangammanavar, H., Eksioglu, S., 2020. Developing childhood vaccine administration and inventory replenishment policies that minimize open vial wastage. Ann. Oper. Res. 292 (1), 215–247.

Barbieri, S., Jorm, L., 2019. Travel times to hospitals in Australia. Sci. Data 6 (1), 1–6.

Biggerstaff, M., Reed, C., Swerdlow, D.L., Gambhir, M., Graitcer, S., Finelli, L., Borse, R.H., Rasmussen, S.A., Meltzer, M.I., Bridges, C.B., 2015. Estimating the potential effects of a vaccine program against an emerging influenza pandemic—United States. Clin. Infect. Dis. 60 (suppl_1), S20–S29.

Brandeau, M.L., Zaric, G.S., Richter, A., 2003. Resource allocation for control of infectious diseases in multiple independent populations: beyond cost-effectiveness analysis. J. Health Econ. 22 (4), 575–598.

Brown, S.T., Schreiber, B., Cakouros, B.E., Wateska, A.R., Dicko, H.M., Connor, D.L., Jaillard, P., Mvundura, M., Norman, B.A., Levin, C., 2014. The benefits of redesigning Benin's vaccine supply chain. Vaccine 32 (32), 4097–4103.

Buccieri, K., Gaetz, S., 2013. Ethical vaccine distribution planning for pandemic influenza: Prioritizing homeless and hard-to-reach populations. Public Health Ethics 6 (2), 185–196.

Carlsson-Szlezak, P., Reeves, M., Swartz, P., 2020. What coronavirus could mean for the global economy. Harv. Bus. Rev. 3, 1–10.

Ceselli, A., Righini, G., Tresoldi, E., 2014. Combined location and routing problems for drug distribution. Discrete Appl. Math. 165, 130–145.

Chartered Association of Business Schools, 2021. Academic journal guide. URL https://charteredabs.org/academic-journal-guide-2021/. (Accessed December 2021).

Chen, X., Li, M., Simchi-Levi, D., Zhao, T., 2020. Allocation of COVID-19 vaccines under limited supply. Available at SSRN 3678986.

Cho, S.-H., Tang, C.S., 2013. Advance selling in a supply chain under uncertain supply and demand. Manuf. Serv. Oper. Manag. 15 (2), 305–319.

Choi, T.M., 2021. Risk analysis in logistics systems: A research agenda during and after the COVID-19 pandemic. Transp. Res. E: Logist. Transp. Rev. 102190, 145.

Chowdhury, P., Paul, S.K., Kaisar, S., Moktadir, M.A., 2021. COVID-19 pandemic related supply chain studies: A systematic review. Transp. Res. E: Logist. Transp. Rev. 102271.

Davila-Payan, C., Swann, J., Wortley, P.M., 2014. System factors to explain 2009 pandemic H1n1 state vaccination rates for children and high-risk adults in US emergency response to pandemic. Vaccine 32 (2), 246–251.

De Boeck, K., Decouttere, C., Vandaele, N., 2020. Vaccine distribution chains in low-and middle-income countries: A literature review. Omega 97, 102097.

Delamonica, E., Minujin, A., Gulaid, J., 2005. Monitoring equity in immunization coverage. Bull. World Health Organ. 83, 384–391.

Dennis, Z.Y., Tang, S.Y., Niederhoff, J., 2011. On the benefits of operational flexibility in a distribution network with transshipment. Omega 39 (3), 350–361.

Deo, S., Manurkar, S., Krishnan, S., Franz, C., 2020. COVID-19 vaccine: Development, access and distribution in the Indian context, no. 378. p. 16.

Department of Health and Human Services, 2020. Hospital locations. URL https://discover.data.vic.gov.au/dataset/hospital-locations-spatial. (Accessed August 2021).

Department of Health Australia, 2021. COVID-19 Deaths by age group and sex. URL https://www.health.gov.au/resources/covid-19-deaths-by-age-group-and-sex{#}:{~}:text=COVID-19deathsbyagegroupandsex, Accessed December 2021.

Dessouky, M., Ordónez, F., Jia, H., Shen, Z., 2013. Rapid distribution of medical supplies. In: Patient Flow. Springer, pp. 385–410.

DHL, 2020. DHL White Paper Delivering Pandemic Resilience. Technical Report, pp. 1–27, URL https://www.dhl.com/global-en/home/insights-and-innovation/thought-leadership/white-papers/delivering-pandemic-resilience.html. (Accessed December 2020).

Duijzer, L.E., van Jaarsveld, W., Dekker, R., 2018. Literature review: The vaccine supply chain. European J. Oper. Res. 268 (1), 174–192.

Ekici, A., Keskinocak, P., Swann, J.L., 2014. Modeling influenza pandemic and planning food distribution. Manuf. Serv. Oper. Manag. 16 (1), 11–27.

Emu, M., Chandrasekaran, D., Mago, V., Choudhury, S., 2021. Validating optimal COVID-19 vaccine distribution models. arXiv preprint arXiv:2102.04251.

Enayati, S., Özaltın, O.Y., 2020. Optimal influenza vaccine distribution with equity. European J. Oper. Res. 283 (2), 714–725.

Eskandarzadeh, S., Eshghi, K., Bahramgiri, M., 2016. Risk shaping in production planning problem with pricing under random yield. European J. Oper. Res. 253 (1), 108–120.

Federgruen, A., Yang, N., 2008. Selecting a portfolio of suppliers under demand and supply risks. Oper. Res. 56 (4), 916–936.

Fidler, D., 2007. Architecture amidst anarchy: global health's quest for governance. 1 Global Health Governance (2007).

Fineberg, H.V., 2014. Pandemic preparedness and response—lessons from the H1N1 influenza of 2009. N. Engl. J. Med. 370 (14), 1335–1342.

Fitzgerald, T.J., Kang, Y., Bridges, C.B., Talbert, T., Vagi, S.J., Lamont, B., Graitcer, S.B., 2016. Integrating pharmacies into public health program planning for pandemic influenza vaccine response. Vaccine 34 (46), 5643–5648.

Foy, B.H., Wahl, B., Mehta, K., Shet, A., Menon, G.I., Britto, C., 2021. Comparing COVID-19 vaccine allocation strategies in India: A mathematical modelling study. Int. J. Infect. Dis. 103, 431–438.

Gamchi, N.S., Torabi, S.A., Jolai, F., 2021. A novel vehicle routing problem for vaccine distribution using sir epidemic model. OR Spectrum 43 (1), 155–188.

Goldstein, E., Wallinga, J., Lipsitch, M., 2012. Vaccine allocation in a declining epidemic. J. R. Soc. Interface 9 (76), 2798–2803.

Goodarzian, F., Ghasemi, P., Gunasekaren, A., Taleizadeh, A.A., Abraham, A., 2021. A sustainable-resilience healthcare network for handling COVID-19 pandemic. Ann. Oper. Res. 1–65.

Govindan, K., Mina, H., Alavi, B., 2020. A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). Transp. Res. E: Logist. Transp. Rev. 138, 101967.

Halper, R., Raghavan, S., 2011. The mobile facility routing problem. Transp. Sci. 45 (3), 413–434.

Huang, H.C., Singh, B., Morton, D.P., Johnson, G.P., Clements, B., Meyers, L.A., 2017. Equalizing access to pandemic influenza vaccines through optimal allocation to public health distribution points. PLoS One 12 (8), e0182720.

IMF, 2020. International monetary fund: The great lockdown: Worst economic downturn since the great depression. URL https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression/. Accessed April 2021.

Jean-Jacques, M., Bauchner, H., 2021. Vaccine distribution—Equity left behind? JAMA 325 (9), 829–830.

Kazaz, B., Webster, S., Yadav, P., 2016. Interventions for an artemisinin-based malaria medicine supply chain. Prod. Oper. Manage. 25 (9), 1576–1600.

Larson, R.C., Teytelman, A., 2012. Modeling the effects of H1N1 influenza vaccine distribution in the United States. Value Health 15 (1), 158–166.

Lee, S., Golinski, M., Chowell, G., 2012. Modeling optimal age-specific vaccination strategies against pandemic influenza. Bull. Math. Biol. 74 (4), 958–980.

Lee, E.K., Pietz, F., Benecke, B., Mason, J., Burel, G., 2013. Advancing public health and medical preparedness with operations research. Interfaces 43 (1), 79–98.

Li, Z., Swann, J.L., Keskinocak, P., 2018. Value of inventory information in allocating a limited supply of influenza vaccine during a pandemic. PLoS One 13 (10), e0206293.

Liao, Q., Ng, T.W., Cowling, B.J., 2020. What influenza vaccination programmes are preferred by healthcare personnel? A discrete choice experiment. Vaccine 38 (29), 4557–4563.

Lima, C.K.T., de Medeiros Carvalho, P.M., Lima, I.d.A.A.S., de Oliveira Nunes, J.V.A., Saraiva, J.S., de Souza, R.I., da Silva, C.G.L., Neto, M.L.R., 2020. The emotional impact of coronavirus 2019-nCoV (new coronavirus disease). Psychiatry Res. 287, 112915.

Longini, J., Ira, M., Halloran, M.E., Nizam, A., Yang, Y., 2004. Containing pandemic influenza with antiviral agents. Am. J. Epidemiol. 159 (7), 623–633.

Lydon, P., Raubenheimer, T., Arnot-Krüger, M., Zaffran, M., 2015. Outsourcing vaccine logistics to the private sector: the evidence and lessons learned from the western cape province in South-Africa. Vaccine 33 (29), 3429–3434.

Mamani, H., Chick, S.E., Simchi-Levi, D., 2013. A game-theoretic model of international influenza vaccination coordination. Manage. Sci. 59 (7), 1650–1670.

Masoumi, A.H., Yu, M., Nagurney, A., 2012. A supply chain generalized network oligopoly model for pharmaceuticals under brand differentiation and perishability. Transp. Res. E: Logist. Transp. Rev. 48 (4), 762–780.

Matrajt, L., Halloran, M.E., Longini, Jr., I.M., 2013. Optimal vaccine allocation for the early mitigation of pandemic influenza. PLoS Comput. Biol. 9 (3), e1002964.

Matrajt, L., Longini, J., Ira, M., 2010. Optimizing vaccine allocation at different points in time during an epidemic. PLoS One 5 (11), e13767.

McMorrow, M.L., Tempia, S., Walaza, S., Treurnicht, F.K., Ramkrishna, W., Azziz-Baumgartner, E., Madhi, S.A., Cohen, C., 2019. Prioritization of risk groups for influenza vaccination in resource limited settings–A case study from South Africa. Vaccine 37 (1), 25–33.

Medlock, J., Galvani, A.P., 2009. Optimizing influenza vaccine distribution. Science 325 (5948), 1705–1708.

Mitchell, S., Andersson, N., Ansari, N.M., Omer, K., Soberanis, J.L., Cockcroft, A., 2009. Equity and vaccine uptake: a cross-sectional study of measles vaccination in Lasbela district, Pakistan. BMC Int. Health Hum. Rights 9 (1), 1–10.

Muckstadt, J., Klein, M.G., Jackson, P.L., Gougelet, R.M., Hupert, N., 2021. Application of supply chain principles to pandemic planning. Available at SSRN 3794252.

National Governors Association Center for Best Practices, 2020. Preparing for the COVID-19 vaccine and considerations for mass distribution. pp. 1–9, URL https://www.nga.org/wp-content/uploads/2020/08/NGA-Memorandum-on-COVID-19-Vaccine-and-Mass-Distribution-Considerations.pdf. (Accessed December 2020).

Niu, B., Li, Q., Chen, L., 2020. Exclusive vs. competitive retailing: overseas vaccine supplier's channel selection considering profit and social responsibility objectives. Comput. Ind. Eng. 144, 106499.

Ozili, P.K., Arun, T., 2020. Spillover of COVID-19: impact on the global economy. Available at SSRN 3562570.

Persad, G., Peek, M.E., Emanuel, E.J., 2020. Fairly prioritizing groups for access to COVID-19 vaccines. JAMA 324 (16), 1601–1602.

Privett, N., Gonsalvez, D., 2014. The top ten global health supply chain issues: perspectives from the field. Oper. Res. Health Care 3 (4), 226–230.

Rachaniotis, N.P., Dasaklis, T.K., Pappis, C.P., 2012. A deterministic resource scheduling model in epidemic control: A case study. European J. Oper. Res. 216 (1), 225–231.

Ramirez-Nafarrate, A., Lyon, J.D., Fowler, O.M., 2015. Point-of-dispensing location and capacity optimization via a decision support system. Prod. Oper. Manage. 24 (8), 1311–1328.

Rao, I.J., Brandeau, M.L., 2021. Optimal allocation of limited vaccine to control an infectious disease: Simple analytical conditions. Math. Biosci. 108621.

Robbins, M.J., Jacobson, S.H., Shanbhag, U.V., Behzad, B., 2014. The weighted set covering game: a vaccine pricing model for pediatric immunization. INFORMS J. Comput. 26 (1), 183–198.

Roy, S., Dutta, R., Ghosh, P., 2021. Optimal time-varying vaccine allocation amid pandemics with uncertain immunity ratios. IEEE Access 9, 15110–15121.

Saif, A., Elhedhli, S., 2016. Cold supply chain design with environmental considerations: A simulation-optimization approach. European J. Oper. Res. 251 (1), 274–287.

Schulte, B., Pibernik, R., 2016. Service differentiation in a single-period inventory model with numerous customer classes. OR Spectrum 38 (4), 921–948.

Seok, H., Nof, S.Y., 2014. Collaborative capacity sharing among manufacturers on the same supply network horizontal layer for sustainable and balanced returns. Int. J. Prod. Res. 52 (6), 1622–1643.

Sridhar, D., Batniji, R., 2008. Misfinancing global health: a case for transparency in disbursements and decision making. Lancet 372 (9644), 1185–1191.

Stone, D., 2002. Policy paradox: The art of political decision making. New york: W. W.

Tanner, M.W., Sattenspiel, L., Ntaimo, L., 2008. Finding optimal vaccination strategies under parameter uncertainty using stochastic programming. Math. Biosci. 215 (2), 144–151.

Tavana, M., Govindan, K., Nasr, A.K., Heidary, M.S., Mina, H., 2021. A mathematical programming approach for equitable COVID-19 vaccine distribution in developing countries. Ann. Oper. Res. 1–34.

Teytelman, A., Larson, R.C., 2013. Multiregional dynamic vaccine allocation during an influenza epidemic. Serv. Sci. 5 (3), 197–215.

Turcotte, J., Harrington, J., Yeager, N., Crowley, K., 2021. Traversing the last mile: A regional health system's experience with Covid-19 vaccine distribution. NEJM Catal. Innov. Care Deliv. 2 (3).

Uribe-Sánchez, A., Savachkin, A., Santana, A., Prieto-Santa, D., Das, T.K., 2011. A predictive decision-aid methodology for dynamic mitigation of influenza pandemics. OR Spectrum 33 (3), 751–786.

Victoria State Government Planning, 2019. Land use and population research. URL https://www.planning.vic.gov.au/land-use-and-population-research/victoria-in-future. (Accessed August 2020).

WHO, 2021a. Coronavirus (COVID-19) dashboard. URL https://covid19.who.int/table. (Accessed February 2021).

WHO, 2021b. The COVID-19 candidate vaccine landscape and tracker. URL https://www.who.int/publications/m/item/draft-landscape-of-covid-19-candidate-vaccines. (Accessed February 2021).

WHO, 2021c. World health organization: Vaccines and immunization, what is vaccination?. URL https://www.who.int/news-room/q-a-detail/vaccines-and-immunization-what-is-vaccination. (Accessed February 2021).

Wu, J.T., Wein, L.M., Perelson, A.S., 2005. Optimization of influenza vaccine selection. Oper. Res. 53 (3), 456–476.

Yadav, P., 2010. Improving public health in developing countries through operations research. In: Wiley Encyclopedia of Operations Research and Management Science.

Yang, Y., Bidkhori, H., Rajgopal, J., 2021. Optimizing vaccine distribution networks in low and middle-income countries. Omega 99, 102197.

Yang, Y., Rajgopal, J., 2021. Outreach strategies for vaccine distribution: A multi-period stochastic modeling approach. In: Operations Research Forum, Vol. 2, no. 2. Springer, pp. 1–26.

Yarmand, H., Ivy, J.S., Denton, B., Lloyd, A.L., 2014. Optimal two-phase vaccine allocation to geographically different regions under uncertainty. European J. Oper. Res. 233 (1), 208–219.