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Research article

Enhancing home delivery of emergency medicine and medical supplies through clustering and simulation techniques: A case study of COVID-19 home isolation in Bangkok

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ABSTRACT

This study investigates the enhancement of the home delivery distribution network for COVID-19 Home Isolation (HI) kits during the Delta variant outbreak of the SARS-CoV-2 virus in Bangkok Metropolitan Area, Thailand. It addresses challenges related to limited resources and delays in delivering HI kits, which can exacerbate symptoms and increase mortality rates. A *k*-means clustering approach is utilized to optimize the assignment of service areas within the COVID-19 HI program, while discrete event simulation (DES) evaluates potential changes in the home delivery logistics network. Real-world data from the peak outbreak is used to determine the optimal allocation of resources and propose a new logistics network based on proximity to patients' residences. Experimental results demonstrate a significant 44.29 % improvement in overall performance and a substantial 40.80 % decrease in maximum service time. The findings offer theoretical and managerial implications for effective HI management, supporting practitioners and policymakers in mitigating the impact of future outbreaks.

1. Introduction

The ongoing COVID-19 pandemic has resulted in a widespread infection of people worldwide. Furthermore, the emergence of a more contagious variant of the SARS-CoV-2 virus has led to a resurgence of COVID-19 cases in various regions, including Thailand. This surge in cases has significantly increased the demand for hospital beds and medical services, overwhelming healthcare facilities, including temporary ones, in many countries [1,2]. To address this strain on healthcare resources, many countries have implemented home isolation (HI) programs for individuals with mild to moderate COVID-19 symptoms, as well as those who are asymptomatic [2–4]. These programs have proven effective in managing limited healthcare resources [5] and have been associated with reduced rates of new COVID-19 infections and mortality [2,6].

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HI programs are an essential option for managing asymptomatic, mild, and moderate COVID-19 patients who do not require hospitalization. Several countries, including Australia, China, Hong Kong, India, and Thailand, have implemented various HI programs in response to the pandemic. In Australia, healthcare providers can send electronic or image-based prescriptions directly to HI patients' phones after a telehealth consultation. These prescriptions can then be electronically sent to pharmacies participating in the temporary COVID-19 Home Medicine Service launched by the Australian Government. Medications are delivered to the patient's address by Australia Post or local delivery services [6]. In China, the government has developed the internet hospital plus drug delivery (IHDD) service to reduce the number of mild symptoms patients at hospitals. Doctors provide medical services and issue online prescriptions via internet hospitals like WeDoctor and Alibaba Health [7]. Patients can receive their medications through home delivery or by self-picking them up at the hospital pharmacy [8]. In Hong Kong, the Home Affairs Department (HAD) has launched the Home Support Supplies Delivery Service for positive COVID-19 cases who need to stay at home or are waiting for hospitals or community isolation. The service can be accessed by calling HAD's hotline, and delivery teams are composed of civil servants and volunteers.

In India, various HI models have been implemented by states in partnership with the private sector and civil society organizations. In Delhi, the national capital, HI services are provided by Portea, a home medical care provider, in collaboration with the Delhi government [9]. Additionally, the non-profit start-up StepOne, a telemedicine platform operated by over 7000 volunteer doctors, provides teleconsultation services to HI patients. COVID-19 HI kits are also distributed by district teams. In Hyderabad, the local government has divided the city into 30 circles under six zones for administrative and development purposes. The medical and health department distributes COVID-19 HI kits according to these Greater Hyderabad Municipal Corporation (GHMC) zones and circles.

In Thailand, the COVID-19 outbreak began in early 2020. Initially, all positive COVID-19 patients, regardless of their symptom severity, were admitted to hospitals or field hospitals. However, in mid-2021, a new variant of the SARS-CoV-2 virus, known as the Delta variant, caused a rapid increase in infections. Bangkok, the capital city, became the area with the highest number of COVID-19 cases in Thailand [10], leading to a shortage of beds in both hospitals and field hospitals for all positive cases. To address this challenge, Thailand launched a home isolation (HI) program for COVID-19 infected individuals. During the initial phase of the HI program in the Bangkok area, the program received support from various government agencies and the private sector. Some healthcare service providers acted as virtual hospitals, utilizing telehealth systems to diagnose, prescribe medications, and monitor symptoms for HI patients. Additionally, volunteers and entrepreneurs, including last-mile delivery service providers and the petroleum business, supported the delivery of medications and other medical supplies to HI patients' homes.

As previously mentioned, the HI program in Thailand relies on the collaboration of various government agencies, private sector entities, and volunteers, including physicians, nurses, pharmacists, and last-mile service providers. These stakeholders can effectively work and communicate remotely through information systems such as telemedicine systems and food or last-mile delivery platforms. While the primary aim of the HI program is to provide timely treatment and medication at home for asymptomatic or mild COVID-19 patients, the program has encountered challenges due to the rapid surge in COVID-19 cases in Thailand. The demand for home isolation has exceeded the current capacity and resources of the program, and there is a shortage of healthcare facilities and supply stocking points. Outbreaks often occur in clusters of more than five infected individuals in the same location [11,12] across the Bangkok Metropolitan Area, leading to prolonged wait times for patients to enter the HI program and delayed medication delivery. These factors increase the risk of severe symptoms or mortality among asymptomatic or mild COVID-19 patients.

Inadequate resource allocation and facility distribution are significant challenges hindering the effective HI services in the Bangkok Metropolitan Area. The high demand for HI services exceeds the availability of resources and facilities dedicated to preparing and distributing essential medicines and medical supplies to patients at home. Currently, facility designations prioritize existing resources rather than incorporating demand-side data such as patient volume and location. This approach creates a logistics facility location problem, where patient locations serve as demand points and healthcare facilities represent corresponding supply points.

While existing literature has explored the effectiveness of HI programs for COVID-19 patients, there is a notable gap in research regarding the optimization of dedicated home delivery logistics networks for COVID-19 HI kits, especially in the context of densely populated areas like the Bangkok Metropolitan Area. This gap is significant because efficient logistics are crucial for ensuring timely and effective treatment for COVID-19 patients in home isolation [13–15]. Optimizing a dedicated home delivery logistics network for COVID-19 HI kits is crucial to overcome these challenges [16–18]. However, the healthcare system typically operates with healthcare personnel who may lack the expertise and resources for optimal logistics management [19]. Without a comprehensive understanding of the logistical challenges and potential solutions, healthcare systems may struggle with delay and inefficiencies in delivering HI kits, which could lead to more severe outcomes and increased transmission rates [14,18].

To address this research gap, it is necessary to identify suitable locations for allocating facilities and resources based on patient demand [20,21]. Unsupervised machine learning algorithms, particularly clustering techniques, offer a well-established approach for tackling facility location and allocation problems [22]. Their applicability extends across diverse research fields. For example, da Costa Borba et al. [20] employed *k*-means clustering to optimize police facility placement in urban areas, while Moskvichev et al. [23] leveraged the same technique to pinpoint optimal locations for container storage and distribution centers, thereby enhancing logistics performance. Similarly, Khalid and Herbert-Hansen [24] advocated for *k*-means clustering as an efficient tool for guiding international location decisions. Yang et al. [25], Huang and Shi [26], and Faezy Razi [27] further showcase the utility of clustering algorithms in reducing costs and elevating service levels within facility location contexts.

Motivated by this research gap and grounded in practical challenges, the central research question arises: How can clustering techniques improve the home delivery logistics network for COVID-19 HI kits in the Bangkok Metropolitan Area? This inquiry delves into applicable techniques and their implementation strategies to enhance network efficiency and ultimately support healthcare personnel in effectively managing the HI program.

The structure of this article is as follows: Section 2 introduces the HI program for COVID-19 patients in the Bangkok Metropolitan

Area, Thailand, and provides a description of the problem. In Section 3, the detailed methodology used to construct the simulation model is presented. Section 4 outlines the clustering technique used in designing the home delivery logistics facility network for COVID-19 HI kits and offers comparison for the simulation scenarios. Section 5 contains a discussion of the findings and their practical implications. Finally, Section 6 elaborates on the conclusions, contributions, and limitations of the study.

2. Home isolation management for COVID-19 patients in the Bangkok Metropolitan Area

In this section, an overview of the COVID-19 home isolation (HI) program in the Bangkok Metropolitan Area is provided, drawing upon a case study of the Pribta Clinic at the Institute of HIV Research and Innovation (IHRI). Additionally, the issue that the study endeavors to address is detailed.

2.1. Home isolation management for COVID-19 patients: A case study of the Pribta Clinic

In response to the surge in COVID-19 cases driven by the Delta variant of the SARS-CoV-2 virus in Thailand, the home isolation (HI) program was launched in August 2021 to alleviate the strain on the limited hospital bed capacity in the healthcare system. This initiative has led to treatment of many patients with mild or asymptomatic COVID-19 cases in their homes. This case study focuses on the Institute of HIV Research and Innovation (IHRI), a non-profit healthcare service provider based in Bangkok that conducts research on HIV and related health issues. IHRI collaborates with other health organizations to enhance the capabilities of community health workers and healthcare providers. The Pribta Clinic, operating under the umbrella of IHRI, acts as a virtual hospital and provides HI services to COVID-19 patients in the Bangkok Metropolitan Area through telemedicine. The clinic handles approximately 70 % of COVID-19 HI cases in the area.

The Pribta Clinic initiates the provision of HI care for COVID-19 patient upon receiving a request through either the National Health Security Office (NHSO) telephone hotline 1330 or the LINE Official Account. Eligible mild or asymptomatic COVID-19 patient are then paired with the Pribta Clinic as their virtual hospital. Patient data is entered into the DMS Home Isolation platform, A-MED Telehealth. A-MED, operated by the Department of Medical Services (DMS) in collaboration with the Ministry of Public Health and National Science and Technology Development Agency (NSTDA) in Thailand, serves as a telemedicine platform connecting volunteer doctors and nurses to prescribe and monitor HI patients. Once a prescription is issued, pharmacists or healthcare workers at the Pribta Clinic access the information via A-MED to verify medication dispensing and check delivery details with the patient by phone. The components of the COVID-19 HI kit, which typically includes favipiravir, paracetamol, nasal decongestants, cough medicines, thermometers, and blood oxygen monitors, are determined based on the patient's symptoms.

The HI kits from the Pribta Clinic are delivered by volunteer drivers to 17 drop-off and pick-up hubs located at gas stations in the Bangkok Metropolitan Area, supported by PTT Oil and Retail Business Public Company Limited. Subsequently, delivery riders from Thai food delivery service platform, UFU, transport the HI kits from the hubs to the patient's home. Throughout the HI treatment, patients report their symptoms to the doctor daily through A-MED Telehealth. The process of the HI program and the logistics network for delivering COVID-19 HI kits are illustrated in Figs. 1 and 2, respectively.

2.2. Problem description of COVID-19 HI kits home delivery service

In this study, the authors analyze the logistics performance of effectively delivering COVID-19 HI kits to home-isolated patients in the Bangkok Metropolitan Area, which has the highest number of COVID-19 cases in Thailand. The focus is on the case study of the

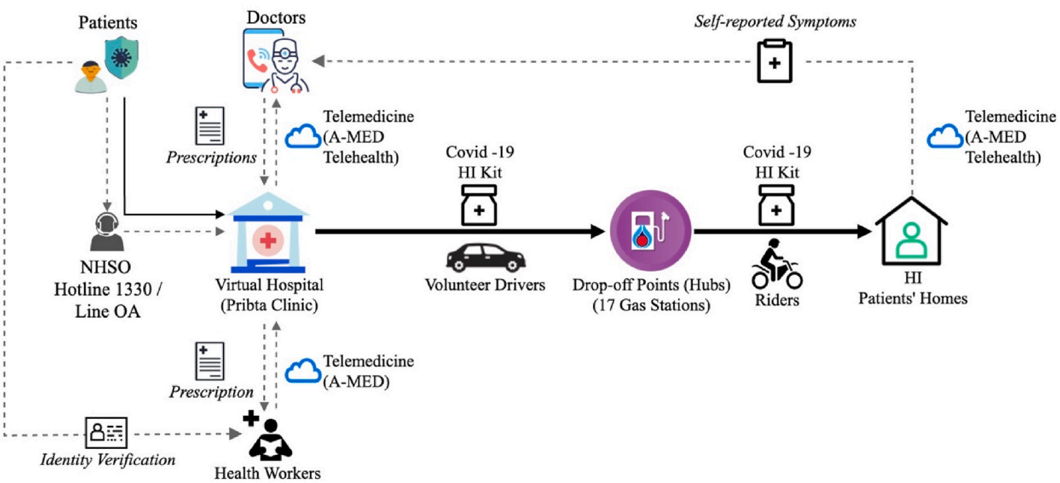


Fig. 1. The process of the HI program and the home delivery logistics network for COVID-19 HI kits of the case study clinic.

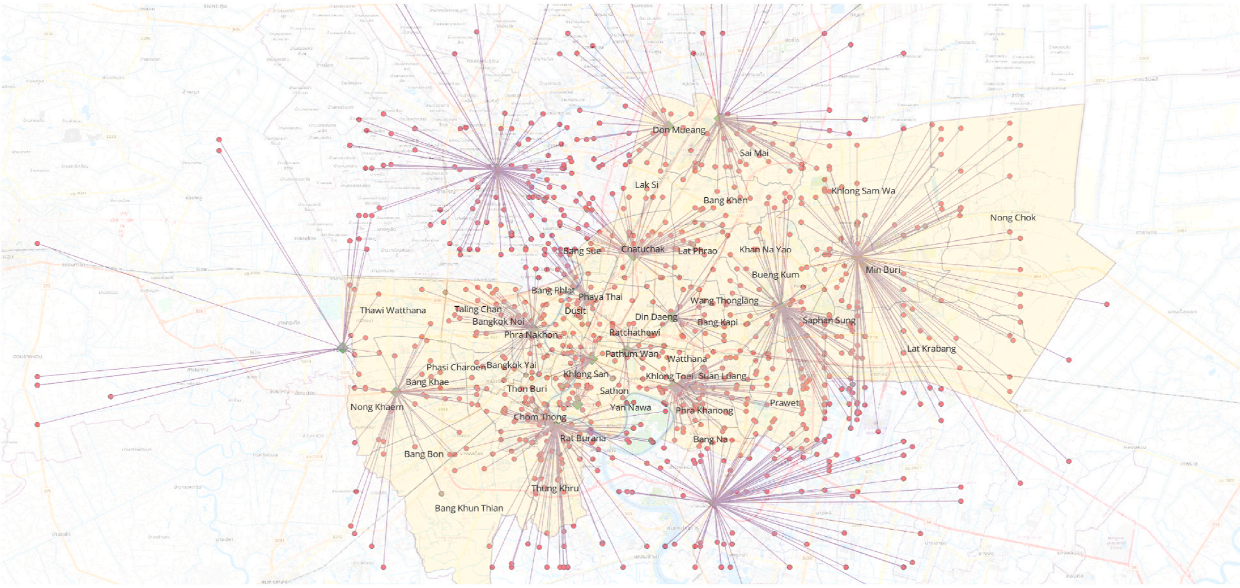


Fig. 2. The home delivery logistics network of COVID-19 HI kits in the Bangkok Metropolitan Area: The case study of the Pribta Clinic.

Pribta Clinic, a virtual hospital that provides HI services and serves the majority of HI patients in the area. Geospatial data is utilized to visualize the COVID-19 HI kits home delivery logistics network, which includes 17 hubs serving as drop-off and pick-up points for HI kits (as depicted in Fig. 2). The daily delivery data of HI kits to patients was obtained from the records of the A-MED Telehealth system during the study period in August 2021, coinciding with Thailand's peak infection rates of the Delta variant of COVID-19 [28].

At the Pribta Clinic, the delivery of COVID-19 HI kits is primarily conducted by volunteer vehicles to 17 hubs and then directly to the respective HI patients by delivery riders employed by a Thai food delivery platform, UFU. The prompt and efficient home delivery of these kits is crucial factor in controlling the spread of the virus. However, the Pribta Clinic faced a challenge of serving 20,000 cumulative COVID-19 HI cases at the early stage of the HI program's launch. An investigation revealed that a significant number of HI patients experienced delays in receiving their HI kits. Consequently, the Pribta Clinic had to reduce the number of patients admitted to its HI service. The situation was further complicated by the rapid and continuous increase in the COVID-19 epidemic, particularly in the Bangkok Metropolitan Area, leaving many positive COVID-19 cases without access to healthcare service providers and unable to enter the HI program.

The delivery of COVID-19 HI kits to patients' homes in the Bangkok Metropolitan Area poses a significant challenge. The Pribta Clinic serves as a central storage facility for medical supplies and inventory items, including the components necessary for preparing COVID-19 HI kits. These kits are then distributed to a large number of patients residing in various locations within the Bangkok Metropolitan Area. The current logistics system for home delivery of the kits requires the clinic to wait for volunteer drivers to pick up the kits and transport them to 17 hubs, strategically located at gas stations. These hubs then serve as drop-off points for delivery riders employed by a Thai food delivery platform. This process results in a significant waiting times for both the clinic and hubs, causing a slow response time that can be detrimental to the health of asymptomatic or mild cases, potentially leading to severe cases or death. Thus, the efficient delivery of medical supplies, medicines, and COVID-19 vaccines is crucial in controlling the spread of disease epidemics [29–31].

Therefore, this study aims to enhance the response time of the home delivery of COVID-19 HI kits in the Bangkok Metropolitan Area by analyzing potential changes in the home delivery logistics facility network. The study proposes relocating and increasing the number of service facilities based on an actual dataset. The phenomenon and performance measures of the proposed system were observed through a discrete event simulation (DES) model. Finally, recommendations for managing the HI program were provided to address future outbreaks or pandemics.

3. Methodology

3.1. Process description for simulation-based analysis

The HI program begins with a service call received at the National Health Security Office (NHSO) through their hotline number (1330) or via the Line OA platform. An NHSO administrator will receive the call from confirmed COVID-19 patients, and mild or asymptomatic cases residing in the Bangkok Metropolitan Area will be assigned to the virtual hospital "Pribta Clinic" for the HI program. Based on the patient's prescription, COVID-19 HI kits are prepared by health workers at the Pribta Clinic for last-mile home delivery. The service process involves four distinct stages, which will be detailed for the purpose of constructing a DES model below.

1) Medical Evaluation and Prescription Generation – A volunteer physician conducts a medical evaluation for HI patients. Subsequently, a prescription is generated through the A-MED Telehealth information system.
2) Preparation of Covid-19 Hi Kits for Dispensing – At the Pribta Clinic, volunteer health workers, including pharmacists and nurses, retrieve the generated prescriptions and prepare COVID-19 HI kits. They then contact the HI patients by telephone to verify their identity and confirm the delivery address for the dispensing of the HI kits.
3) Sorting and Delivering of Covid-19 Hi Kits to Drop-Off and Pick-Up Locations (Hubs) – The prepared COVID-19 HI kits are sorted at the Pribta Clinic and sent to various drop-off and pick-up locations, referred to as hubs. These hubs are located at gas stations in the Bangkok Metropolitan Area and are grouped into 17 categories based on destination locations. Daily, between 7:00 a.m. and 10:00 a.m., a volunteer driver collects the HI kits from the Pribta Clinic and delivers them to the respective hubs.
4) Last-Mile Delivery – Upon reaching the hub, the COVID-19 HI kits are transported to the HI patient's doorstep by a delivery rider.

The objective of the system is to ensure the prompt delivery of drugs and medical supplies to HI patients. Therefore, the performance of the COVID-19 HI kit home delivery service is primarily evaluated by determining the length of time patients must wait for the kit after their prescription has been generated. The patient care process of the HI program at the Pribta Clinic, as previously described, is depicted through a conceptual model, which is a logical representation of the system, as shown in Fig. 3.

3.2. DES model development and validation

In the model, the entities are the patients and their COVID-19 HI kit. These entities are processed by resources of the system at the clinic and hubs, including volunteer physicians, pharmacists, nurses, volunteer drivers, and delivery riders. To simulate the system, the authors adopted the discrete event simulation approach and developed the model using ProModel, simulation-based software for improving supply chain systems. The model's data input is sourced from both primary and secondary data. Primary data was obtained through in-depth interviews with a volunteer physician participating in the HI program at the Pribta Clinic. Additionally, data retrieved from the A-MED telehealth information system in August 2021 was utilized to determine the patient arrival cycle time, the average evaluation and prescription process time, and the patient's residence locations. Following data fitting, Table 1 summarizes the model inputs based on the data collected during the current clinic operations at each stage of service.

As displayed in Table 1, Stage 3 involves the transportation of the prepared HI kits from the Pribta Clinic to 17 hubs within the Bangkok Metropolitan Area by volunteer drivers using their personal vehicles. Seven main routes have been identified, as illustrated in Fig. 4, and each route contains 1 to 4 stops with a travel time ranging from 30 to 80 min, inclusive of loading and unloading time. The estimated travel distance and time data were obtained from Google Maps, and a summary of the delivery routes for the COVID-19 HI kits from the Pribta Clinic to the hubs can be found in Table 2.

In the final stage, State 4, the delivery of COVID-19 HI kits to patients is accomplished through a last-mile delivery process executed by a delivery rider. The coverage areas for the last-mile delivery of HI kits by each hub location vary and are contingent upon the administrative districts in Bangkok and surrounding metropolitan provinces. To determine the estimated travel time from each hub to the various districts, data was gathered from Google Maps and excludes any toll road routes. The routes and estimated travel times for delivering the COVID-19 HI kits from the hubs to the patients' homes are presented in Table 3.

Subsequently, the authors integrated actual data obtained from the computerized records of the A-MED telehealth system to determine the patient arrival cycle. For the purposes of the study, data from August 2021 was used due to the prevalence of the highly infectious Delta variant in Thailand during that time. The Pribta Clinic, serving as a virtual hospital, accepted 1124 positive COVID-19 cases into the HI program. The previously presented conceptual model initiates with the creation of a prescription by volunteer doctors through the A-MED telehealth system. Table 4 illustrates the approximate percentage distribution of patient arrival cycles over a 24-h period.

The simulation model was developed based on the following initial assumptions: (1) adequate availability of inventory items for preparing COVID-19 HI kits; (2) disregard of shift change durations; (3) use of Google Maps to estimate travel times between origin and destination points; (4) exclusion of vehicle refueling downtime, as it is performed during driver or rider releases; (5) assumption of no heavy rain during shipping and the ability of riders to deliver HI kits by motorcycle; (6) exclusion of vehicle repair downtime, with the assumption of immediate replacement in the case of a disabled vehicle; (7) exclusion of emergency scenarios such as accidents, floods, and transport network shutdowns; (8) assumption of a rider's ability to successfully deliver HI kits in all cases.

After data fitting, the validation of the DES model was carried out. This is a crucial step in ensuring the reliability of the simulation results and their applicability in decision-making [32–34]. The validity of the conceptual model and input data was assessed by employing the facility trace command in the ProModel software. A normality test was conducted to evaluate the adequacy of the

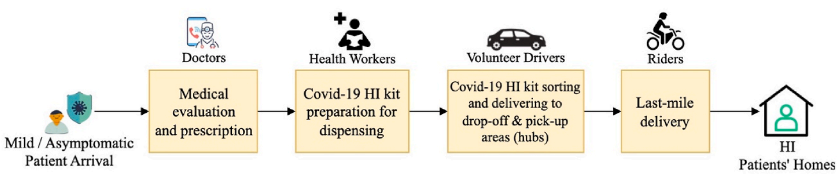


Fig. 3. A conceptual model for simulation modelling.

Table 1
The model inputs from the current service operations of the Pribta Clinic.

Model input	Value	Unit	Operating schedule
Stage 1: Medical evaluation and prescription generation:			
Number of volunteer physician	100	Person	Everyday
Evaluation and prescription time	Weibull(432, 0.507)	min/order	24 h
Stage 2: Preparation of COVID-19 HI kits for dispensing:			
Number of health workers	6	Person	Everyday
HI kit preparation time	10	min/order	7:00 a.m.–5:00 p.m.
Stage 3: Sorting and delivering of COVID-19 HI kits to drop-off and pick-up locations (hubs)			
Number of transport routes	7	Route	Everyday
Number of trips (personal car)	Uniform(0,2)	Trip/hour	7:00 a.m.–10:00 a.m.
Loading time	20	min	
Unloading time	20	min	
Travel time (clinic to hub)	Based on destination location (see in Table 2)	min	
Stage 4: Last-mile delivery			
Number of trips (motorcycle)	Uniform(4,5)	Trip/hour	Everyday
Number of hubs	17	Hub	11:00 a.m.–11:00 p.m.
Loading time	10	min	
Unloading time	5	min	
Travel time (hub to destination)	Based on destination location (see in Table 3)	min	

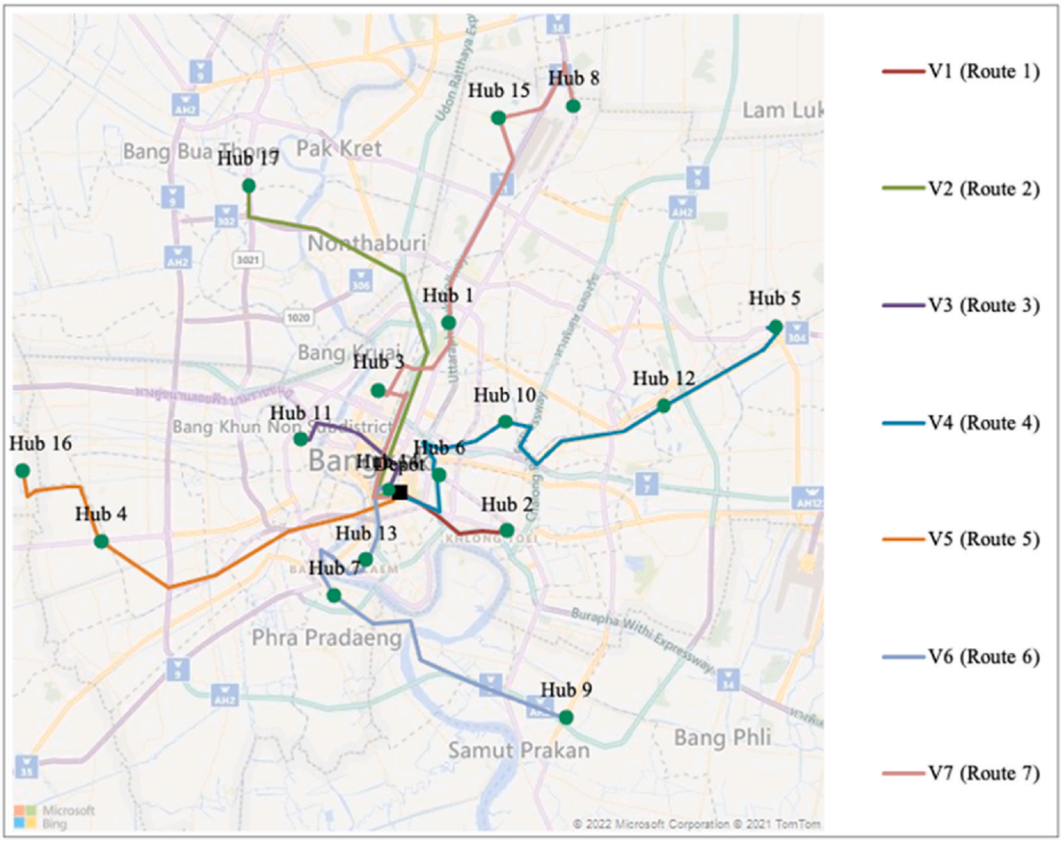


Fig. 4. Transport routes for delivering HI kits from the Pribta Clinic to hubs.

model. The average total service cycle time for both actual and simulated system data were tested for normality. The validation results indicated that there was no difference between the actual and simulated data. Besides, the simulation study requires the determination of an appropriate number of replications to ensure the accuracy and precision of the simulation outcomes [35–37]. The replication process serves to measure the variance of means obtained from the simulation. An increased number of replications can minimize error [38–40]. In this study, the optimal number of replications was determined in accordance with Kelton et al. [38]. Hence, 130 replications were conducted over a three-month simulation period to attain the desired level of statistical confidence and generate the data set for one scenario.

Table 2
The routes for delivering COVID-19 HI kits from the Pribta Clinic to hubs.

#No. Route	Number of stops	Location	Distance travelled (km) (from the Pribta Clinic)	Accumulated travel time (min)	Volume of load (%)
1	1	Hub 2	7.40	30	8.32
2	1	Hub 17	30.4	47	5.69
3	2	Hub 14	1.70	8	2.35
		Hub 11	10.80	42	9.81
4	4	Hub 6	6.3	25	3.03
		Hub 10	15.0	36	7.52
		Hub 12	25.9	60	5.82
		Hub 5	35.7	80	7.90
5	2	Hub 4	20.3	53	4.92
		Hub 16	31.8	71	4.24
6	3	Hub 13	7.3	20	4.36
		Hub 7	15.6	35	10.83
		Hub 9	38.5	74	7.58
7	4	Hub 3	8.4	27	1.95
		Hub 1	15.8	46	6.06
		Hub 15	32.1	71	3.87
		Hub 8	43.6	87	5.75

3.3. *Determining facility locations in the home delivery logistics network of COVID-19 HI kits through k-means clustering*

Naturally, the spread of COVID-19 often occurs in clusters, which are defined as groups of five or more cases linked to a common source of exposure [11,12,41]. In the Bangkok Metropolitan Area of Thailand, a large number of COVID-19 clusters have been identified across various locations. To address this situation, a new logistics network system for home delivery of COVID-19 HI kits is proposed. The system involves the relocation and increase in the number of HI clinics that functions like the Pribta Clinic. The optimal number and locations for these new clinics were determined based on the number of patients under the supervision of the Pribta Clinic. The goal of this approach is to shorten the waiting time for patients to receive their HI kits. The performance of the proposed system was evaluated through simulations that varied the allocation of resources. The methodology for determining the optimal number and locations of new clinics and the simulation scenarios are described in detail below.

The location of clinics plays a critical role in designing an efficient logistics and supply chain network, as highlighted in various studies [42,43]. To address this, *k*-means clustering algorithm was applied to determine the number and location of HI clinics in the Bangkok Metropolitan Area, Thailand. *K*-means is a widely used and simple unsupervised machine learning technique, commonly used for partitioning a large dataset into distinct groups, known as clusters [20,24,44]. It is particularly suitable for handling large datasets with more than 200 points ($n \geq 200$) and has been extensively employed in spatial partition problems due to its implementation ease and efficiency [24,45,46]. The *k*-means algorithm adjusts the position of data points based on their distance, forming *k* clusters with centroids as the mean of each cluster. The nearest centroid is then assigned to each data point based on the Euclidean distance, resulting in the division of data points into *k* clusters [45]. Given a set of data points, *k*-means clustering aims to optimize the objective function as follows:

$$J = \sum_{j=1}^{k} \sum_{i \in C_j} \left\| x_i - \mu_j \right\|^2 \tag{1}$$

where J is the criterion function to minimize the distance between each data point and the centroid of the cluster, x_i is the ith data points, μ_j is the jth centroid of the cluster, C_j is the set of data points of the jth cluster, and k represents the number of clusters [47,48]. The *k*-means algorithm is shown in Table 5.

In *k*-means clustering analysis, a critical consideration is the selection of an optimal value for the number of clusters, denoted as k [50,51]. This step involves employing two methods: the Elbow method and Silhouette coefficient analysis, which are widely used for determining the optimal number of clusters in a dataset [52–54]. The Elbow method examines the variance explained as a function of the number of clusters, aiming to identify the point where adding another cluster does not significantly improve the explanation of variance [54]. On the other hand, Silhouette coefficient analysis assesses the quality of clustering by measuring the cohesion and separation of clusters [54]. By combining these two techniques, more reliable and robust clustering outcomes can be achieved, providing a strong indication of the optimal number of clusters [53,54].

4. Results

This research aims to improve the delivery of COVID-19 HI kits to patients in the Bangkok Metropolitan Area by suggesting a new logistics facility network. The proposed approach entails increasing the number of virtual hospitals, similar to the Pribta Clinic, to enhance the speed and effectiveness of the home delivery service. Consequently, this section identifies potential locations and the optimal number for virtual hospitals based on their proximity to the HI patients' residences. This approach seeks to minimize travel time and enhance the service's overall performance.

Table 3
The routes and the estimated travel time for the last-mile delivery of COVID-19 HI kits from hubs to HI patients' homes in each district.

Origin	Destination zone		Travel time (min)
	District	Province	
Hub 1	Chatuchak	Bangkok	13
	Bang Sue	Bangkok	8
	Lak Si	Bangkok	17
	Lat Phrao	Bangkok	25
	Bang Khen	Bangkok	32
Hub 2	Phra Khanong	Bangkok	21
	Suan Luang	Bangkok	20
	Bang Na	Bangkok	27
	Prawet	Bangkok	37
	Lat Krabang	Bangkok	41
Hub 3	Dusit	Bangkok	1
	Pom Prap Sattru Phai	Bangkok	18
	Phra Nakhon	Bangkok	19
	Samphanthawong	Bangkok	25
Hub 4	Nong Khaem	Bangkok	6
	Bang Khae	Bangkok	9
	Phasi Charoen	Bangkok	22
Hub 5	Min Buri	Bangkok	6
	Khlong Sam Wa	Bangkok	19
	Nong Chok	Bangkok	21
Hub 6	Khlong Toei	Bangkok	11
	Watthana	Bangkok	26
Hub 7	Rat Burana	Bangkok	15
	Bang Khun Thian	Bangkok	14
	Thung Khru	Bangkok	19
	Bang Bon	Bangkok	20
	Phra Pradaeng	Samut Prakan	29
Hub 8	Mueang Pathum Thani	Pathum Thani	45
Hub 9	Mueang Samut Prakan	Samut Prakan	8
Hub 10	Huai Khwang	Bangkok	2
	Wang Thonglang	Bangkok	12
	Din Daeng	Bangkok	23
	Ratchathewi	Bangkok	32
	Phaya Thai	Bangkok	29
Hub 11	Bangkok Noi	Bangkok	9
	Bangkok Yai	Bangkok	15
	Khlong San	Bangkok	18
	Bang Phlat	Bangkok	12
	Thon Buri	Bangkok	23
	Chom Thong	Bangkok	24
Hub 12	Saphan Sung	Bangkok	21
	Khan Na Yao	Bangkok	18
	Bang Kapi	Bangkok	18
	Bueng Kum	Bangkok	22
Hub 13	Bang Kho Laem	Bangkok	4
	Bang Rak	Bangkok	13
	Yan Nawa	Bangkok	18
Hub 14	Pathum Wan	Bangkok	13
	Sathon	Bangkok	16
Hub 15	Don Mueang	Bangkok	3
	Sai Mai	Bangkok	43
Hub 16	Thawi Watthana	Bangkok	11
	Taling Chan	Bangkok	27
	Mueang Samut Sakhon	Samut Sakhon	46
	Mueang Nakhon Pathom	Nakhon Pathom	36
Hub 17	Mueang Nonthaburi	Nonthaburi	14

4.1. *Clustering analysis*

The initial step in *k*-means clustering analysis is to determine the optimal number of clusters. The study first applied the Elbow method. However, the results indicated that the Elbow method was not able to accurately determine the number of clusters in the dataset. The optimal number of clusters was not clearly discernible, as depicted in Fig. 5a. Therefore, the study additionally employed Silhouette coefficient analysis to compare the values. The combination of the Elbow and Silhouette methods suggested the optimal number of clusters to be four, as illustrated in Fig. 5a and b.

The *k*-means algorithm was then applied to the dataset to cluster COVID-19 HI patients in the Bangkok Metropolitan Area using

Table 4
Patient arrival cycles.

Time slot	Percentage	Time slot	Percentage
00:01–01:00	1.05	12:01–13:00	11.06
01:01–02:00	0.30	13:01–14:00	8.28
02:01–03:00	0.08	14:01–15:00	7.37
03:01–04:00	0.00	15:01–16:00	8.09
04:01–05:00	0.00	16:01–17:00	7.98
05:01–06:00	0.00	17:01–18:00	7.34
06:01–07:00	0.45	18:01–19:00	5.38
07:01–08:00	2.03	19:01–20:00	5.87
08:01–09:00	2.07	20:01–21:00	5.64
09:01–10:00	4.14	21:01–22:00	3.54
10:01–11:00	6.09	22:01–23:00	3.39
11:01–12:00	7.15	23:01–00:00	2.71

Table 5
k-means clustering algorithm [49].

Algorithm I *k*-means clustering algorithm
1: Specify the number k of clusters to assign.
2: Initialize k cluster centroids $\mu_1, \mu_2, \ldots, \mu_k, \in \mathbb{R}^n$ randomly.
3: FOR: Each cluster
4: REPEAT:
5: From k cluster, assign each point to its closet centroid.
6: Calculate the new centroid or mean of each cluster.
7: UNTIL: The centroid positions do not change.
8: ENDFOR

Python. The authors determined $k = 4$ as the optimal number of clusters (iterations), based on the results from the Elbow and Silhouette methods.

In this case study, 1124 data points were examined to assign each point to its nearest centroid. The *k*-means analysis revealed four centroid values, representing potential coordinates for new HI clinic locations to distribute COVID-19 HI kits to HI patients in each cluster. These locations are located in four different districts within the Bangkok Metropolitan Area: Prawet (PR), Bang Khae (BK), Mueang Nonthaburi (MN), and Khlong Sam Wa (KS), as illustrated in Fig. 6.

Table 6 displays the four newly established clinic locations for HI patients, along with the proportion of HI patients in each cluster and the fitting distribution of service time for last-mile delivery.

4.2. Simulation results

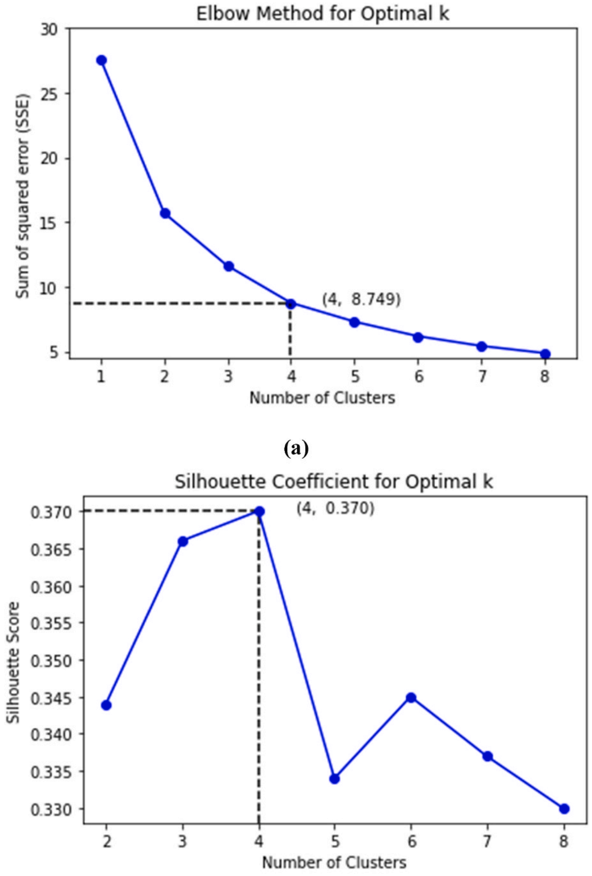
With the addition of new HI clinics, the 17 hubs currently serving as drop-off and pick-up points for COVID-19 HI kits across the Bangkok Metropolitan Area can be removed from the logistics network. This eliminates the need to transport HI kits to the hubs, enabling direct delivery from each HI clinic to the patients' residences via a rider. To evaluate the impact of this change on the service time of COVID-19 HI kit home delivery, a scenario analysis was conducted using a simulation model. The authors varied three parameters: the number of health workers at each potential HI clinic, the number of trips per hour for last-mile delivery, and the rider's work schedule. Four scenarios were proposed based on the new logistics facility network system, altering the number of resources (health workers and rider trips per hour). Parameter values were randomly assigned based on the number of patients visiting each HI clinic. Table 7 presents the scenarios studied through the variation of resources.

Based on the provided data, simulation models were developed using ProModel software, and 130 three-month replications were conducted for each scenario to assess the impact of variations on the system. The results indicate that the proposed logistics network for managing the home delivery of COVID-19 HI kits in the Bangkok Metropolitan Area can significantly enhance service responsiveness.

In Scenarios 1 to 4, hubs were removed from the network, and HI clinics were added at 1 to 4 locations, respectively. Scenarios 1 and 2 were compared, with both scenarios having the same number of last-mile delivery trips per hour but varying in the number of health workers. Scenario 2 increased the number of health workers at three potential locations (BK, MN, and KS) from 1 to 2. The simulation results show that compared to the base case scenario, the average service time for last-mile HI kit delivery can be improved by at least 35.07 % (from 1.29 to 0.84 days) in these two scenarios. However, the simulation also results indicates that the system in Scenarios 1 and 2 becomes saturated, with no further improvement even when the number of resources is increased.

In Scenarios 3 and 4, the number of trips per hour to the HI clinic locations was increased, resulting in a slightly improved average service time of 35.57 % and 36.03 %, respectively, compared to Scenarios 1 and 2.

Following the initial simulation outcomes from Scenarios 1 to 4, two additional scenarios were formulated by modifying the operating schedule for last-mile delivery. This adjustment extended the delivery timeframe from a 12-h period (11:00 a.m. to 11:00 p.m.) to a 15-h window (8:00 a.m. to 11:00 p.m.), while maintaining the same parameter values from Scenarios 1 and 4 in Scenarios 5



(a)

(b)

Fig. 5. Optimal number of clusters (k = 4) for the k-means clustering analysis by the Elbow Method (a) and the Silhouette coefficient analysis (b).

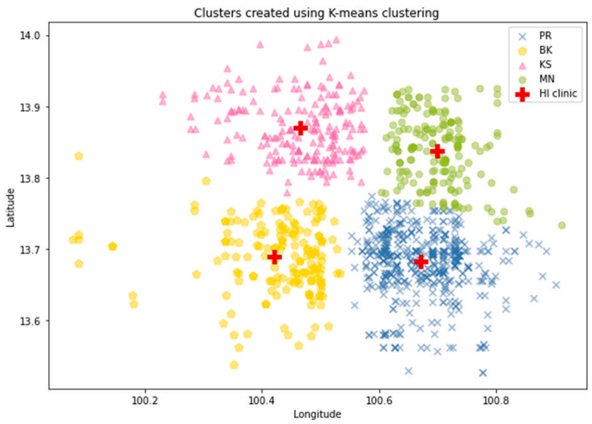


Fig. 6. Clusters created using k-means clustering.

and 6, respectively. These additional test scenarios are presented in Table 8.

Extending the operating schedule for last-mile delivery in Scenarios 5 and 6 further optimized the performance of the COVID-19 HI kit home delivery system. Scenario 5 demonstrates the highest level of performance, with COVID-19 HI kits delivered to patients within 17.24 h, or approximately 0.72 days, representing a 44.29 % improvement over the base case scenario. Additionally, this scenario exhibits the shortest maximum service time among all test scenarios, with a maximum time of 22.11 h or 0.92 days for COVID-19 HI kits home delivery. This marks a significant decrease of 40.80 % from the maximum service time of 37.35 h in the base case

Table 6
The results of the *k*-means clustering analysis.

Potential Location	GPS Coordinates	Province	The Proportion of HI patients	Service Time for Last-mile Delivery (min)
PR	13.68291572, 100.6717611	Bangkok	53.74 %	Weibull (0.243, 1.7, 15.7)
BK	13.6884868, 100.42061153	Bangkok	15.03 %	Weibull (1.41, 2, 19)
MN	13.8699108, 100.46540711	Nonthaburi	17.26 %	Weibull (0.856, 1.74, 19.1)
KS	13.839316, 100.69801513	Bangkok	13.97 %	Erlang (−1.39, 4, 4.77)

Table 7
Parameter values at different levels for scenario analysis.

	Potential location	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Number of health workers	PR	3	3	3	3
	BK	1	2	2	2
	MN	1	2	2	2
	KS	1	2	2	2
Number of trips per hour for last-mile delivery	PR	5	5	5	5
	BK	2	2	3	4
	MN	2	2	3	4
	KS	2	2	3	3

scenario. Therefore, Scenario 5 facilitates rapid delivery of COVID-19 HI kits to HI patients. The simulation results for various parameter values are summarized in Table 9.

Fig. 7 illustrates a comparison of the service time for all test scenarios, representing the time between a volunteer doctor creating a prescription and a HI patient receiving their medication. The boxplots show the average service time for HI kit delivery and its standard deviation, with the whiskers indicating the minimum and maximum service times of the simulation runs for each scenario.

The study findings indicate that increasing in the number of HI clinics and the implementing effective location strategies can significantly reduce the lead time for home delivery of COVID-19 HI kits and enhance responsiveness. However, it is noted that adding resources such as health workers and last-mile delivery trips and hours, does not have a significant impact on the system's performance. The average response time for the service can be improved by a maximum of 16.53 %, with a limit of not exceeding 2.85 h, when comparing the best scenario (Scenario 5) to the worst scenarios (Scenarios 1 and 2). According to the case study data, the delivery of HI kits to patients can be achieved within a 24-h period in all simulated system scenarios.

5. Discussion and research implications

This research aims to propose improvements to the home delivery logistics network for COVID-19 HI kits in Thailand. By examining the management of HI services during the COVID-19 pandemic through a real-life case study, the empirical analysis identifies that the slow service response time is due to the high number of dispersed HI patients and resource constraints. The study suggests the necessity of establishing a new logistics facility location for delivering COVID-19 HI kits to patients' homes, utilizing clustering and simulation techniques. The research findings contribute to both theoretical and managerial implications, providing practical recommendations as follows.

5.1. Theoretical implications

The study makes significant theoretical contributions by integrating concepts from healthcare management and logistics, thereby bridging the gap between these two fields. It demonstrates the effectiveness of clustering techniques in optimizing healthcare logistics networks. Specifically, the article applies the *k*-means clustering method with real-world data to address the facility location problem in logistics network design. This technique has been widely used in spatial clustering [55]. In recent studies, *k*-means clustering has

Table 8
The additional test scenarios by adjusting the operating schedule for last-mile delivery.

	Potential location	Scenario 5	Scenario 6
Number of Health workers	PR	3	3
	BK	1	2
	MN	1	2
	KS	1	2
Number of trips per hour for last-mile delivery	PR	5	5
	BK	2	2
	MN	2	2
	KS	2	2
Operating schedule for last-mile delivery		08:00 a.m.–11:00 p.m.	08:00 a.m.–11:00 p.m.

Table 9
Summary of simulation results.

Parameter value	Base case	Scenarios					
		1	2	3	4	5	6
Number of HI clinics	1	4	4	4	4	4	4
Number of health workers	6	PR 3 BK 1 MN 1 KS 1	PR 3 BK 2 MN 2 KS 2	PR 3 BK 2 MN 2 KS 2	PR 3 BK 2 MN 2 KS 2	PR 3 BK 1 MN 1 KS 1	PR 3 BK 2 MN 2 KS 2
Number of drop-off and pick-up areas (hubs)	17	–	–	–	–	–	–
Number of trips per hour for delivering to a hub	1–2	–	–	–	–	–	–
Number of trips per hour for last-mile delivery	4–5	PR 5 BK 2 MN 2 KS 2	PR 5 BK 2 MN 2 KS 2	PR 5 BK 3 MN 3 KS 3	PR 5 BK 4 MN 4 KS 3	PR 5 BK 2 MN 2 KS 2	PR 5 BK 2 MN 2 KS 2
Operating period for last-mile delivery (hours)	12	12	12	12	12	15	15
The average service time (min)	1856.96	1205.55	1205.55	1192.37	1187.82	1034.55	1047.05
Minimum service time (min	2241.02	1470.74	1470.74	1469.91	1469.91	1326.88	1351.31
Maximum service time (min)	1697.42	1095.02	1095.01	1187.82	1095.01	915.01	915.01
% Improvement from base case	–	35.07 %	35.07 %	36.03 %	35.57 %	44.29 %	43.61 %

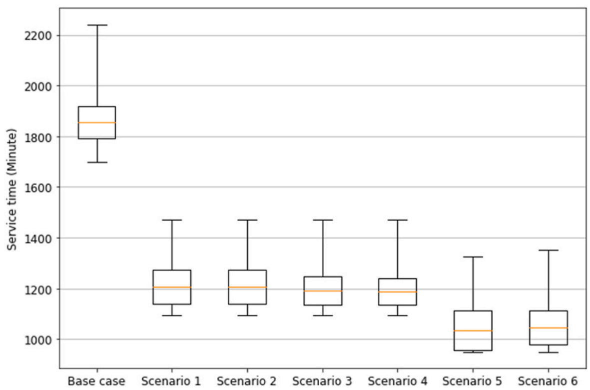


Fig. 7. Comparison of service time of the test scenarios.

been utilized in various decision problems within healthcare context. For example, Belhor et al. [56] used *k*-means clustering for home healthcare routing and scheduling problems. Wang et al. [57] applied this method to determine candidate locations for the selection of appropriate private clinic locations. In Jakarta Indonesia, Setiawan et al. [58] used *k*-means and Fuzzy C-Means (FCM) for clustering hospitals to allocate human health resources appropriately.

Furthermore, the study conducts simulation experiments to optimize resource allocation within the logistics facility network system. The proposed new logistics facility network system, with optimized resource allocation, facilitates faster access to medication, thereby reducing the risk of progression from mild or asymptomatic cases to severe illness or death.

However, the proposed approach aims to provide healthcare personnel with a simple understanding and application of clustering techniques, including scenario analysis by adjusting resources to streamline their service operations during pandemic incidents. While the current study focuses on basic clustering techniques, there is potential for implementing advanced clustering techniques to further improve the analysis results. The methodology and findings of this study can contribute to the development of decision support systems for healthcare logistics, providing a valuable framework for future research in this area.

5.2. Managerial implications and practical recommendations

Practically, the study offers guidance for managing healthcare systems during pandemics. Its methodology can assist practitioners and decision-makers in making operational choices for efficient HI management amid fluctuating patient numbers. In preparation for future outbreaks, the study provides managerial implications and practical recommendations for designing an effective logistics facility network for the home delivery of COVID-19 HI kits, as follows.

1) Collect demand-side data of HI COVID-19 patients

Upon the initiation of the HI program in Thailand, healthcare professionals and other partners had to provide treatment and medication dispensing to patients from multiple locations. This necessitated the integration of virtual healthcare facilities into the operational framework of the HI system. To address this challenge, Thailand established a call center in the form of a hotline, Line OA, and the A-MED Telehealth telemedicine platform to effectively manage the treatment and personal information of HI COVID-19 patients. The recorded information, which includes patient treatment details and location addresses, is stored in a comprehensive database. The substantial volume of patient data generated through this system allows for rapid identification of infection clusters and demand for medication supplies through data analysis by relevant parties.

2) Apply a data analytic algorithm to find the optimal facility locations for supporting COVID-19 HI kits home delivery service

In this study, the authors utilized cleansed, accurate, and current demand-side data of COVID-19 patients in the Bangkok Metropolitan Area to conduct data analytics. An unsupervised machine learning algorithm, *k*-means, was applied to determine the optimal numbers and locations of healthcare facilities that can effectively serve the needs of COVID-19 patients. The implementation of this approach has the potential to improve the operational efficiency of the COVID-19 response program and help prevent the spread of future infectious diseases. Furthermore, future research could greatly benefit from the application of state-of-the-art algorithms in analyzing the logistics facility network design problem, leading to more accurate computation.

3) Collaborate with partners and stakeholders for setting up an urgent logistics facility network system

In the face of the COVID-19 pandemic, establishing a streamlined logistics network system requires collaboration among various partners and stakeholders. Existing healthcare facilities have proven insufficient in meeting the demands of infected patients who require immediate treatment or quarantine, necessitating the provision of medical services outside of healthcare facilities, such as homes and community isolations. To achieve this goal, the active involvement of multiple parties is imperative. Government agencies, such as the Department of Medical Services (DMS), the Department of Disease Control (DDC), and the National Health Security Office (NHSO), need to establish standard guidelines for infectious disease treatment and comprehensive care for patients. Likewise, the Thailand Center for COVID-19 Situation Administration (CCSA), chaired by the Prime Minister, plays a key role in increasing public awareness of the pandemic situation and home-based treatment procedures. Private sector entities or state-owned enterprises can also make a substantial contribution in the logistics system, including healthcare service providers, drugstores, Thailand Post, and other transport and logistics service providers. As demonstrated by the case study of the Bangkok Metropolitan Area, it exemplifies the potential of private organizations to coordinate the logistics system by leveraging their resources and expertise, such as technology and facilities, financial support, and human capital. In conclusion, the collaboration of various actors, including government agencies, private organizations, and volunteers, is vital for the effective operations of the logistics system [59]. These actors work together from various locations to provide medical treatment and deliver medicines and medical supplies to quarantined patients.

4) Determine the optimal number of resources at each facility location using simulation

The optimization of healthcare facility locations and the appropriate allocation of resources are critical elements in delivering effective healthcare services during outbreaks such as the COVID-19 pandemic. In this study, the authors adopt a data-driven approach using the unsupervised machine learning technique of clustering analysis to identify the optimal locations for service facilities and to increase their number. The proposed logistics facility system is then evaluated through discrete even simulation (DES) to determine the optimal resource allocation. Through this approach, the authors aim to provide relevant agencies with a strategy for allocating resources effectively at each facility location in response to evolving epidemic situations, thereby enhancing the response time of HI services.

5) Integrate facilities and medication supplies management

The HI program's implementation necessitates the selection of a physical healthcare facility to function as a virtual hospital. COVID-19 HI patients' prescriptions are issued at their respective hospitals or clinics and then delivered to their homes. Consequently, it is crucial to determine the requisite number of healthcare workers and volunteers, including pharmacists, nurses, and delivery personnel, relative to the volume of HI patients, under the supervision of a medical facility. This research utilized real-world case study data to develop a new logistics network system for the home delivery of COVID-19 HI kits in the Bangkok Metropolitan Area. The results indicate that increasing the number of medical facilities and optimizing resource allocation can improve service efficiency. However, government agencies must play a pivotal role in identifying the locations and quantity of medical facilities to serve as virtual hospitals, as well as in allocating necessary resources. Moreover, each facility should function as a hub for the last-mile home delivery service and must have sufficient storage for medications and medical supplies.

Furthermore, the allocation and distribution of special controlled drugs, such as Favipiravir and Molnupiravir, which are exclusively controlled by Thailand's Government Pharmaceutical Organization (GPO), must be carefully considered. Due to the limited availability of these drugs for COVID-19 patients, it is crucial to clearly define the criteria for matching HI patients with each virtual hospital. HI patients should be assigned to nearby facilities, and each virtual hospital should admit a cumulative number of patients that aligns with its available capacity.

However, financial considerations are often overlooked in emergency situations. Logistics networks and facilities are typically supported and subsidized by volunteers, government agencies, and private sectors. Therefore, in the future, the management of facilities and medication supplies must also include financial aspects to ensure the efficiency of healthcare logistics systems [60]. This entails considering the costs associated with setting up and maintaining virtual hospitals, procuring medications and supplies, and compensating personnel, including health workers and volunteers. Understanding and managing these financial aspects are crucial for optimizing resource allocation, securing adequate funding for operations, and maximizing the impact of healthcare logistics efforts, particularly during crisis situations like the COVID-19 pandemic [59].

6. Conclusions

The ongoing COVID-19 pandemic continues to have a significant impact globally, with a surge in cases and facilities despite the passage of time since its initial outbreak in 2019. This has led to the adoption of a "new normal" in daily life, including work from home and online education [30,61]. The pandemic has severely strained healthcare systems, resulting in shortages of medical supplies, hospital beds, and healthcare professionals [62,63]. This shortage can lead to increased mortality rates from COVID-19 infection and other illnesses, such as cancer [64,65].

Effective management of healthcare facilities is crucial in addressing this global crisis, prompting the widespread implementation of home quarantine and isolation as a strategy for managing the pandemic [66]. The use of technology and information systems, such as telemedicine, application platforms, and call centers, has facilitated the timely delivery of medical care to a large number of patients. However, the successful implementation of HI programs requires the seamless integration and coordination of all services, including admission, medication preparation, and transportation, to minimize the severity of symptoms in patients.

During a severe COVID-19 outbreak in Thailand, the HI system was hastily developed to manage the rapidly increasing number of COVID-19 cases in various areas. This study focuses on the challenges faced in managing HI through a case study of the Pribta Clinic in central Bangkok. The clinic functions as a virtual hospital, integrating a pharmaceutical inventory within the HI system to provide pharmaceutical preparation and delivery of drugs and medical supplies to nearly all HI patients in the Bangkok Metropolitan Area. However, the locations of COVID-19 outbreak clusters are constantly changing and vary in size, and most health workers and operators in the HI system are volunteers. Consequently, planning a flexible distribution of COVID-19 HI kits presents a complex challenge due to resource constraints and uncertainty. The design of an efficient logistics network is crucial for any organization aiming to enhance customer response time [43,67,68].

This article proposes a method for determining facility locations and allocating resources in the logistics network of the HI system in the Bangkok Metropolitan Area. Using case study data, potential facility locations that can function as virtual hospitals and hubs for the last-mile delivery of COVID-19 HI kits can be identified spatially using a clustering algorithm such as *k*-mean. Additionally, simulation analysis was utilized to determine the optimal number of resources at each stage of the logistics network. These techniques serve as valuable and widely used analytical tools in pandemic or disaster preparedness plans [69,70]. The experimental results can assist decision-makers in the better planning of HI management.

Concisely, the study makes several key contributions.

- Utilizing cluster analysis and simulation with real-world data to improve the HI system during the COVID-19 pandemic.
- Examining the effects of different resource levels (e.g. number of HI clinics, health workers, frequency of last-mile delivery trips, and operating schedules) on the response time for delivering COVID-19 HI kits.
- Proposing a simulation method for efficiently allocating resources to HI system facilities, thereby minimizing idle resources and delays. Resources requirements are based on the number of registered HI patients.
- Providing theoretical and managerial insights for establishing a logistics facility network system for HI management in future infectious disease outbreaks or health emergencies, such as the monkeypox in multiple countries.

The study has a notable limitation as it does not consider the financial aspect, particularly delivery and distribution costs, due to the unavailability of cost information. These costs are crucial in the operations of a healthcare supply chain, encompassing both storage and transportation costs [71]. A cost-effective distribution system is essential for a successful logistics plan [4,71]. However, the COVID-19 pandemic has led to a sudden increase in demand for essential healthcare products, such as anti-viral drugs, pulse oximeters, and ventilators, which are critical for patient care [72]. Providing timely treatment to COVID-19 patients with asymptomatic, mild, and moderate symptoms through the HI program is crucial for reducing the risk of hospitalization and mitigating the impact of the virus. Therefore, patient response time is a critical non-financial indicator for evaluating healthcare system performance [4,72–74].

The simulation analysis could be enhanced with more accurate and up-to-date data to provide practical solutions for decision-makers and healthcare providers. Another limitation is the determination of geographical locations of the proposed new HI clinics, which were scientifically identified through clustering algorithms. In practice, a site survey would be needed to identify nearby existing medical facilities that could collaborate as HI clinics. Additionally, future research could improve the analysis of logistics network design problems by utilizing state-of-the-art algorithms for more precise results.

Ethics declarations

This study was conducted in accordance with the declarations of Helsinki. The research design and ethical considerations were subject to review and approval by the Mahidol University Central Institute Review Board (Protocol number: MU-CIRB 2021/415.2709).

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Data availability statement

The data supporting the findings of this study are available from the BDMS Health Research Center, Bangkok Dusit Medical Service (BDMS), Bangkok, Thailand. However, the data are not publicly available due to their containing information that could compromise personal information.

CRediT authorship contribution statement

Duangpun Kritchanchai: Visualization, Validation, Supervision, Funding acquisition, Conceptualization, Methodology. **Rawinkhan Srinon:** Writing – review & editing, Visualization, Validation, Funding acquisition, Conceptualization, Project administration. **Pongtorn Kietdumrongwong:** Visualization, Conceptualization, Data curation. **Jirawan Jansuwan:** Software, Formal analysis. **Nittaya Phanuphak:** Conceptualization, Data curation. **Wirachchaya Chanpuypetch:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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