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Research article

Exact Modeling and Solution of the Healthcare Facility Location-Allocation and Vehicle Routing Problem for Medication Delivery through Rural Primary Care Units

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Abstract: This study aims to analyze the optimal locations of Subdistrict Health Promoting Hospitals (SHPHs) for participating in the "Taking Medicine Nearby House" project by systematically allocating patients to appropriate SHPHs and formulating efficient delivery routes aimed at enhancing home based healthcare services for chronic disease patients particularly whom diagnosed with hypertension in Hat Yai District, Songkhla Province, with a focus on individuals facing mobility limitations. The research proposes a conceptual framework integrating spatial analysis and operations research techniques to improve community-level healthcare logistics. A two-stage solution was applied to solve the problem with the Location and Allocation Model and the Vehicle Routing Model. The first model selected the optimum location of SHPH and allocated patients to that location. The latter provided the medication distribution routing to each SHPS's patient. The exact method solved with LINGO satisfies the case study solution. The results indicate that, among nine candidate SHPHs, six were identified as optimal locations to participate in the service. Fifty-eight patients were effectively allocated to these facilities under capacity constraints, achieving a minimized total transportation and operational cost of 123,149.37 THB (1.000 THB = 0.02990 USD). The findings demonstrate that applying the Location Allocation Problem (LAP) and Vehicle Routing Problem (VRP) through exact solution methods can effectively support planning and logistics management in home-based healthcare systems and can provide potential for application in other regional contexts in the future.

Keywords: Location allocation problems; vehicle routing problems; exact method; home healthcare; medication delivery

1. Introduction

Currently, public hospitals in Thailand, particularly large- scale hospitals, are facing overcrowding due to the high volume of outpatient visits. In 2017, the public health service system under the Ministry of Public Health recorded up to 220 million outpatient visits annually. On average, regional hospitals served 3,152 outpatients per day, large general hospitals served 1,709 per day, and small general hospitals served 1,204 per day [1]. Although the number of outpatients in regional and general hospitals has shown a continuous downward trend between 2022 and 2024 for example, the average number of outpatients at regional hospitals decreased from 23,022 per day in 2022 to 15,490 in 2023, and it is projected to further decrease to 13,341 in 2024; while general hospitals saw a decline from 29,299 outpatients per day in 2022 to 20,303 in 2023, with an expected further drop to 18,709 in 2024 [2]. However, the volume of service users remains high, leading to persistent overcrowding in public hospitals. This overcrowding directly contributes to prolonged waiting times, delayed access to healthcare services, diminished quality of care, and increased patient dissatisfaction. The root causes of these issues primarily lie in the limitations of available resources and shortages of medical personnel. To address these challenges, strengthening the primary healthcare system, particularly through the family practice teams and community health service networks, has been recognized as a key strategy. This approach facilitates the redistribution of healthcare workloads away from hospitals, reduces the number of outpatient visits, and promotes a more continuous and accessible care system. It is especially beneficial for patients with chronic conditions, who can receive consistent and community-based care [3].

In 2017, the Ministry of Public Health announced a policy aimed at reducing hospital overcrowding by encouraging patients to receive medications outside of hospital settings through the "Taking Medicine Nearby House" project. This initiative allows patients to present prescriptions and receive medications at licensed community pharmacies, rather than having to wait for hospital-based medication delivery. The program primarily targets patients with chronic diseases who are free from complications and require continuous medication. This approach reflects the concept of healthcare supply chain management, which plays a crucial role in supporting home healthcare services, particularly for elderly patients or those unable to travel to obtain their medications. However, the implementation of this program has led to increased costs within the healthcare service system, particularly in logistics and pharmaceutical distribution. These costs encompass transportation, storage, and the delivery of medications, medical supplies, and equipment directly to patients' homes. Notably, transportation costs account for approximately 47.3% of total logistics expenditures in Thailand, representing a critical factor that must be effectively managed to control healthcare expenses and enhance the efficiency of the service system [4–6].

Hat Yai Hospital is a regional-level hospital providing healthcare services throughout Hat Yai District, Songkhla Province. According to data from the Ministry of Public Health in 2023, the hospital recorded a total of 1,117,720 service visits per year, with 70.45% originating from Hat Yai District, 14.93% from other districts within Songkhla Province, and 14.62% from other provinces. Although the hospital is officially equipped with approximately 700 beds, the actual utilization reached as high as 1,000 beds, resulting in a bed occupancy rate of 111.6%, which exceeds its service capacity [7]. Regarding outpatient services, the hospital recorded 235,280 outpatients in 2020, 223,200 in 2021, and 199,378 during the first half of 2022, averaging approximately 3,500 patients per day, significantly higher than its intended capacity of 2,500 patients per day. In 2020, a total of 1,805 patients participated in the "Taking Medicine Nearby House" project, ranking as the second-highest in the country. However, the implementation of the program in Hat Yai District continues to encounter challenges related to the geographical distribution of participating pharmacies. As there is no limitation on the number of pharmacies permitted to join the program, an imbalance in distribution has emerged. Urban areas such as Hat Yai, Kho Hong, Khlong Hae, and Khlong U-Taphao Subdistricts exhibit a high concentration of participating pharmacies. This oversaturation results in low patient volumes for some pharmacies, prompting their withdrawal from the program. Conversely, rural areas—including Khue Tao, Nam Noi, Tha Kham, Thung Yai, Chalung, Thung Tam Sao, Khuan Lang, Ban Phru, and Phatong—experience limited participation, compelling residents to travel considerable distances to access services. This situation contributes to increased transportation costs for patients.

In response to the challenges above, a medication delivery model involving Subdistrict Health Promoting Hospitals (SHPHs) has been proposed as part of the "Taking Medicine Nearby House" project. Under this model, SHPHs serve as central hubs for distributing medications to patients within their designated service areas. Village Health Volunteers (VHVs) are assigned to deliver medications, provide basic healthcare, and continuously monitor patients' health conditions to enhance the efficiency and coverage of healthcare services. Based on the findings from previous evaluations of the project, it has been observed that in urban areas, medications can be effectively distributed through community pharmacies due to their widespread availability and relatively high density. However, in peripheral or suburban areas, the number of participating pharmacies is considerably limited, thereby restricting patients' access to medication services in these regions, as illustrated in Figure 1. Consequently, this study focuses on exploring and proposing suitable location management strategies for primary healthcare units, namely Subdistrict Health Promoting Hospitals (SHPHs), to serve as distribution points in the "Taking Medicine Nearby House" project. The research particularly targets rural areas within Hat Yai District, Songkhla Province, encompassing nine subdistricts: Khue Tao, Nam Noi, Tha Kham, Thung Yai, Chalung, Thung Tam Sao, Khuan Lang, Ban Phru, and Phatong. A medication distribution model via subdistrict-level SHPHs is developed in parallel with a delivery route planning strategy to ensure that medications are delivered efficiently and comprehensively to patients, especially since most of the program's beneficiaries are elderly individuals who are unable to travel to receive their medications.

The primary objective of this study is to enhance healthcare accessibility by addressing LAP and VRP. This is achieved through the development and analysis of a mathematical model that employs exact methods to determine the most cost-effective solution, thereby resulting in an efficient medication distribution system, reduced operational costs, and improved quality of public health services at the community level.

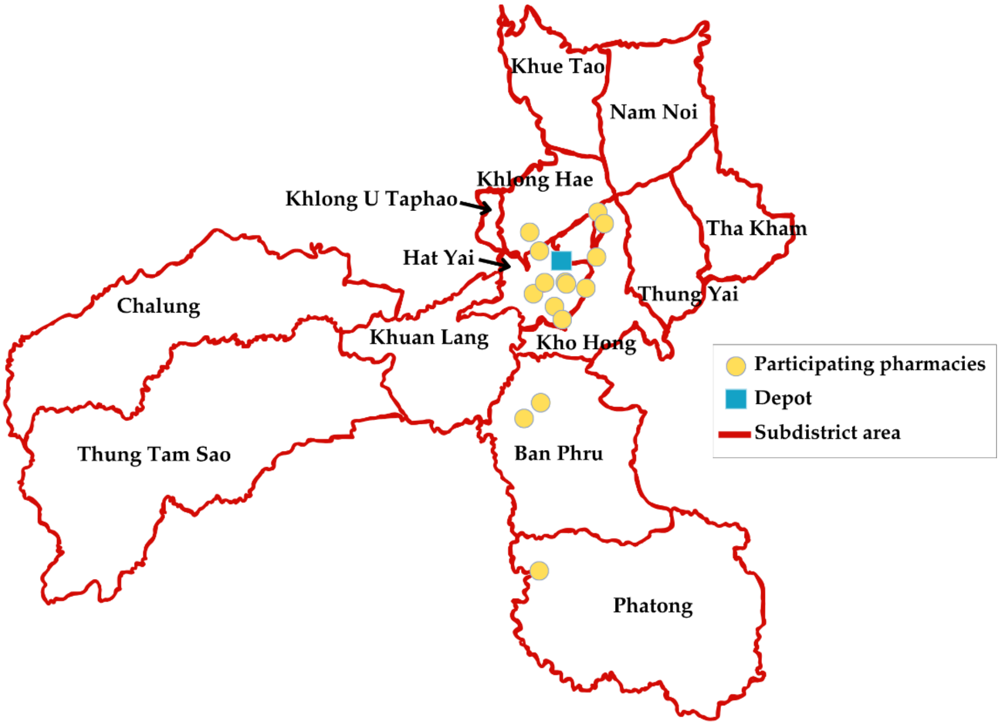

Figure 1. The Distribution of Pharmacies in the "Taking Medicine Nearby House" project, Hat Yai District, Songkhla Province.

This research proposes a novel medicine distribution model tailored to the Thai primary healthcare system. In this model, Subdistrict Health Promoting Hospitals (SHPHs) function as local distribution hubs, while Village Health Volunteers (VHVs)—who already provide home-based care—are engaged to deliver medicines directly to patients. This integration not only improves the efficiency and coverage of home healthcare services but also strengthens supply chain resilience by utilizing established community-based health infrastructures to maintain service continuity during disruptions. Furthermore, the study addresses LAP and VRP associated with medicine distribution through SHPHs. Mathematical modeling techniques are applied, and an exact method is employed to determine optimal facility locations and delivery routes, ensuring cost-effective and reliable healthcare logistics in a community context.

2. Materials and methods.

2.1 Integrated community and home-based healthcare systems

In recent years, home-based healthcare systems have garnered significant attention, especially for patients suffering from chronic illnesses and those with limited mobility. These systems are increasingly viewed as essential in enhancing healthcare accessibility, alleviating pressure on primary hospitals, and ultimately improving patients' quality of life. A critical enabler of this shift is the development of efficient healthcare logistics, particularly in terms of optimizing the delivery of medical services and medications directly to patients' homes. Several studies have explored various computational approaches to improve the efficiency and effectiveness of home healthcare logistics. For example, Phonin et al. [8] addressed VRP with Time Windows (VRPTW) in home healthcare, proposing a hybrid Tabu Search and Greedy Algorithm to minimize vehicle service time. Their method reduced the number of required vehicles by up to 59%, demonstrating strong potential for operational efficiency. Similarly, Atta et al. [9] explored the broader Home Health Care Routing and Scheduling Problem (HHCRSP), aiming to reduce costs, enhance service quality, and maintain care continuity. The evaluation of various algorithmic approaches highlighted the critical role of HHCRSP in delivering cost-effective, patient-centered home healthcare. Suwatcharachaitiwong et al. [4] studied systems that integrate both direct home delivery and patient self-collection from nearby pickup points, such as lockers or convenience stores. The study aimed to minimize total operational costs using a Genetic Algorithm. Simulation results indicated that the algorithm was effective in optimizing delivery logistics, supporting flexible models of medication distribution tailored to patients' needs and locations. In Kordi et al. [10], a multi-objective mixed-integer mathematical model was developed to optimize home healthcare service planning. For small-scale problems, they applied the epsilon-constraint method using CPLEX software. At the same time, for larger, real-world scenarios, they introduced a Multi-Objective Variable Neighborhood Search (MOVNS) algorithm to explore solution spaces effectively. The approach emphasized the need for adaptable and scalable algorithms capable of balancing multiple, often competing planning objectives. Addressing the challenges of uncertainty in home healthcare operations, Abdul Nasir and Kuo [11] proposed a chance-constrained optimization model that considered multi-depot and multi-period factors alongside precedence constraints. They developed a specialized three-stage solution methodology combined with stochastic simulation to enable robust and flexible planning under uncertain conditions. Expanding on technological innovations in healthcare logistics, Euchi et al. [12] explored the use of telemedicine and artificial intelligence (AI) to support home healthcare delivery, particularly for elderly patients. The research introduced AI-driven routing and scheduling techniques based on autonomous learning and search algorithms, enhancing decision-making in distributed healthcare environments and optimizing patient visit allocations.

The advancement of community-based healthcare models has played a vital role in strengthening healthcare systems by leveraging local resources and positioning sub-district health centers as central service hubs. Effective implementation requires coordinated planning of facility locations, patient distribution, and service routing. Addressing these needs, Ransikarbum et al. [13] proposed a dual-phase approach combining K-means clustering for hospital siting and a time-constrained CVRP model for pharmaceutical distribution. The method demonstrated practical effectiveness in both medium-term facility planning and short-term logistics. Salami et al. [14] developed a Multi-Period Capacitated Maximal-Covering Location-Allocation model that accounts for the dynamic nature of healthcare demand over time. By incorporating capacity constraints across multiple planning periods, their model ensures continuity of care and optimal allocation of limited healthcare resources. The approach utilizes Mixed-Integer Linear Programming (MILP), a method well-suited for solving complex, NP-hard problems in urban healthcare service design. In the realm of advanced delivery technologies, Shi et al. [15] introduced a bi-objective mixed-integer programming model for multi-trip drone routing with simultaneous pickup and delivery, demonstrating improved delivery speed, safety, and efficiency through a modified NSGA-II algorithm. Similarly, Zaid et al. [16] addressed the Home Healthcare VRP (HHCVRP) with a focus on social sustainability, employing a hybrid metaheuristic combining Ant Colony Optimization and Non-Dominated Sorting to enhance service quality and workload management in smart city contexts. The studies highlight the value of advanced optimization and emerging technologies in developing efficient, adaptable, and sustainable community-based healthcare systems.

2.2 Review of literature on location-allocation and vehicle routing problems in healthcare logistics

This section reviews key studies that apply location-allocation and vehicle routing models to optimize healthcare logistics, demonstrating their effectiveness in improving service coverage, resource allocation, and operational efficiency for example, the case study by Phutthaphooltrakun & Raothanachonlakul [17] applied the Maximal Covering Location Problem (MCLP) model to plan the locations of blood storage and distribution centers in Thailand. The model improved service coverage to 96.66%, demonstrating the potential of LAP in designing public health infrastructure. Tapabut et al. [18] studied the relocation of emergency parking stations by incorporating the elderly population as a key factor in the target area. Using LAP for analysis, the study aimed to allocate service points that better meet the specific needs of this demographic group. In the context of pharmacy management, Poomisirisawat et al. [19] proposed a Location-Inventory Problem (LIP) model that integrates the selection of pharmacy locations with optimal inventory level planning. An exact method was used to enhance the efficiency of medication distribution, reduce operational costs, and increase medication accessibility for patients in the area. Similarly, Pan et al. [20] applied the LAP model to analyze the coverage of tertiary hospitals in major cities across China, with a focus on equitable distribution and improving access to healthcare services. In the field of emergency management, Alghanmi et al. [21] examined the allocation of Points of Dispensing (PODs) for distributing medications and medical supplies during emergencies. Their approach prioritized population risk levels to ensure a rapid and effective response. Zhuo et al. [22] proposed a Multi-Objective LAP model for planning new community hospitals in Wuhou District, Chengdu, aiming to align hospital capacity with population needs and to enhance the quality and long-term efficiency of the healthcare system. Meanwhile, Murad et al. [23] analyzed the impact of location on healthcare accessibility by introducing a P-Median model for determining the locations of health service centers in Jeddah, Saudi Arabia. The model was designed to ensure that residents could access services within a 15-minute walking distance, underscoring the importance of spatial planning in promoting equity in access to basic healthcare services.

Shi et al. [24] investigated routing and scheduling for medicine delivery in home healthcare systems under demand uncertainty and developed a hybrid genetic algorithm to enhance routing decision efficiency. Similarly, Al Theeb et al. [25] proposed a multi-objective mixed-integer linear programming model that integrates a two-echelon VRP for vaccine supply chains in developing countries, aiming to reduce the number of undelivered vaccines. Euchi et al. [26] developed a VRP approach incorporating time windows and synchronized visits for home healthcare systems using artificial intelligence (AI) techniques to optimize scheduling and reduce operational costs. Durak et al. [27] introduced a mathematical model for routing and scheduling nurses' visits by considering ergonomic factors through a Fuzzy Inference System to evaluate workload suitability in the context of home healthcare services. Furthermore, HadjTaieb et al. [28] proposed a shortest-path routing approach for home healthcare providers using alternative energy vehicles under the Green VRP with Time Windows concept, which emphasizes reducing environmental impact and promoting the sustainability of out-of-hospital medical service systems.

Exact methods in healthcare logistics primarily utilize MILP and professional-grade solvers (such as CPLEX or Gurobi), employing techniques such as branch-and-bound, branch-price-and-cut, set-partitioning, or commodity-flow formulations to examine all feasible routes and determine the global optimum for VRP or HHCRSP problems. However, computational complexity increases rapidly as the number of patients or service networks expands, limiting optimal problem-solving to small-scale instances (typically not exceeding 50 patient nodes on average) due to the exponential growth in complexity. Research by van Montfort et al. [29] and recent work by Zhang & Zhang [30] indicate that optimal solutions can be obtained from deterministic models for small-scale instances, but for large-scale problems or those involving uncertainty, metaheuristics such as VNS provide superior results in terms of efficiency and scalability. Studies on exact solution methods, which can be applied to various logistics problems, have been extensively explored. Paradiso et al. [31] proposed an exact solution framework for the multi-trip VRP with time window constraints, focusing on urban logistics systems and last-mile delivery. Their model involves many variables and constraints. Salavati-

Khoshghalb et al. [32] applied an exact method to solve VRP under demand uncertainty. They developed an Integer L-shaped algorithm within a Branch-and-Cut framework and incorporated a return travel cost approximation technique to improve cost reduction efficiency. Zetina et al. [33] introduced an exact algorithm for the non-convex quadratic facility location problem, capable of handling instances with up to 1,000 nodes while accounting for the interaction costs between service centers and customers. Balti & Jemai [34] conducted a comprehensive study reviewing various approaches to the VRP and proposed a hybrid methodology that integrates exact optimization methods with Home Health Care (HHC) systems and Intelligent Transportation Systems (ITS) using Internet of Things (IoT) technologies. This approach enhances routing reliability for home healthcare service vehicles by accounting for traffic density and enabling real-time route adjustments to avoid congestion. Similarly, Zhang & Zhang [30] addressed the Vehicle Routing and Appointment Scheduling Problem (VRASP), aiming to optimize caregiver routing and appointment scheduling to reduce operational costs and improve service quality. The proposed solution, a customized Variable Neighborhood Search (VNS) algorithm combining regret-based insertion and Tabu Search, serves as a practical decision-support tool for HHC providers operating under uncertain conditions. In a related study, Linfati et al. [35] developed a two-phase heuristic algorithm for scheduling and routing in pharmaceutical delivery to highly dependent patients. The model, designed for daily visit scheduling, uses a flexible mathematical framework applicable to various scenarios. Hybrid metaheuristics—specifically, Simulated Annealing combined with Record-to-Record Travel—are employed to refine initial solutions, enhancing overall delivery efficiency. Van Montfort et al. [29] focused on the development of routing and scheduling plans for home-based caregiving services. The study introduced two MILP models—the Miller-Tucker-Zemlin (MTZ) and time-indexed formulations—demonstrating their effectiveness in reducing required staff, lowering service costs, and improving caregiver-task alignment. Notably, the research highlighted that the advantages of task division are not only dependent on the planning objective but also yield benefits when minimizing travel time.

The growing complexity of home healthcare logistics has driven research toward advanced optimization models that integrate routing and scheduling. These studies predominantly employ hybrid methodologies combining exact algorithms, heuristics, and real-time data from ITS and IoT technologies. Such approaches enhance service delivery by addressing dynamic factors including traffic, patient-specific needs, and caregiver capabilities. Moreover, these models extend beyond conventional routing problems by incorporating appointment scheduling, task allocation, and community-based frameworks. Collectively, they underscore the vital role of hybrid optimization and real-time data integration in improving the efficiency, flexibility, and quality of home healthcare logistics. Table 1 summarizes a comparative analysis of recent key studies on Location-Allocation and Vehicle Routing Problems and their extensions within home healthcare. It highlights variations in problem scope, target populations, planning levels, methodologies, and innovations, while indicating the use of real data and community health resources such as Subdistrict Health Promoting Hospitals (SHPHs) and Village Health Volunteers (VHVs).

Table 1. Comparative Overview of Studies on Location-Allocation and Vehicle Routing Problems in Home Healthcare

Researcher / Year	Problem Scope	Target Group	Planning Level	Problem Addressed	Methodology	Real Data	Uses SHPH /VHV	Key Innovation
van Montfort et al. (2024)	Integrating task-splitting into HHC routing & scheduling	Patients receiving HHC	Operational	VRPTW	MILP + Heuristics	✗	✗	Task splitting & managing temporal dependencies
Phonin et al. (2025)	Minimizing total completion time in HHC services	Elderly patients	Operational	VRPTW	Tabu Search with Greedy list	✗	✗	Fast metaheuristic for route efficiency
Atta et al. (2025)	Efficient routing & caregiver allocation	HHC patients	Operational	HHCRSP	Exact + Heuristics/ Metaheuristics	✗	✗	Integrating caregiver allocation in VRP
Kordi et al. (2023)	Multi-objective HHC optimization (cost, CO_2, workload, quality)	Patients needing HHC	Operational	Multi-objective VRP	ε-constraint + MOVNS	✗	✗	Balancing multiple real-world healthcare objectives
Abdul Nasir et al. (2024)	Mobile health facility placement & uncertain supply routing	Priority HHC patients	Strategic & Operational	Multi-depot VRP	Chance-constrained + Simulation	✓	✗	Uncertainty & disruption-focused HHC model
Zaid et al. (2024)	Real-time VRP for smart city HHC	Urban patients	Operational	HHCVRP	ACO + NSGA	✗	✗	Sensor data integration & social sustainability
Ransikarbum et al. (2024)	Hospital location & medicine distribution	Drug retailers & patients	Midstream & Last-mile	CVRP + Facility Location	K-means + CVRP + GIS	✓	✗	GIS-aided model with clustering & routing

Table 1. Comparative Overview of Studies on Location-Allocation and Vehicle Routing Problems in Home Healthcare (Continues)

Researcher / Year	Problem Scope	Target Group	Planning Level	Problem Addressed	Methodology	Real Data	Uses SHPH /VHV	Key Innovation
Shi et al. (2022)	Drone-based medicine delivery during emergencies	Communities during crises	Emergency Logistics	Drone Location Routing Problem	Bi-objective MIP + NSGA-II	✗	✗	Multi-trip drone model with pick-up & delivery
Euchi et al. (2020)	Routing & scheduling for vulnerable populations	Elderly, mobility-limited	Operational	HHC Routing & Scheduling	AI-based Learning & Search	✗	✗	Pure AI-driven solution without mathematical models
Balti & Jemai (2025)	VRP with real-time traffic adaptation	HHC patients	Operational	Traffic-aware VRP	Exact + ITS	✗	✗	Integration of Intelligent Transport Systems (ITS)
Schneider et al. (2019)	Overview of VRP research	General logistics sector	N/A	VRP overview	Editorial/Review	✗	✗	Heuristic and exact methods in the VRP landscape
Zhang & Zhang (2025)	Routing & appointment scheduling under uncertainty	Aging population	Operational	VRASP	Stochastic + VNS (Hybrid)	✗	✗	Combining stochastic modeling with regret-based heuristics
Linfati et al. (2018)	Scheduling & delivery routing for medication	Highly dependent patients	Operational	Medication Delivery VRP	2-Phase Heuristic (SA + RTR)	✓	✗	Cluster-based daily routing for medicine delivery
This Research	**Optimal SHPH location + routing for hypertension patients**	**Chronic disease patients with limited mobility**	**Strategic & Operational**	**LAP + VRP (medication delivery model)**	**Exact (LINGO) + GIS**	✓	✓	**Novel model integrating LAP + VRP with a real community-based health system**

* VHV (Village Health Volunteers)

* SHPH (Subdistrict Health Promoting Hospitals)

2.3 Application of healthcare logistics in the "taking medicine nearby house" project

This study presents an approach for applying the concepts of the Location Problem and the Routing Problem to enhance service efficiency under the "Taking Medicine Nearby House" project, with a primary focus on the actual residential locations of patients. The proposed approach aims to improve medication accessibility, reduce the burden of travel to main hospitals, and strengthen the role of Subdistrict Health Promoting Hospitals (SHPHs) as key health service distribution points within communities. A significant challenge in the program implementation lies in the SHPHs' site selection, where it is appropriate in both geographical location and service capacity to function effectively as service units under the program. Additionally, the optimal design of medication distribution routes, utilizing locally available resources such as VHVs, presents further complexity. Observations from the program's implementation in recent years indicate that the government has engaged private-sector pharmaceutical suppliers to be responsible for the procurement and distribution of medications to participating pharmacies, where patients can collect their prescribed medications directly. This service model is well-suited to urban contexts, as patients' residences are typically located near participating pharmacies. Conversely, in rural or suburban areas, the number of participating pharmacies is limited, resulting in patients having to travel long distances to access medication services. This has become a significant barrier to achieving equitable access to healthcare services.

To enhance access to healthcare services for people living in rural areas, the researcher proposes the concept of utilizing SHPHs as the primary local units for medication distribution, in place of pharmacies. Under this approach, suppliers would be responsible for distributing medications from central facilities to selected SHPHs. VHVs would then be assigned to deliver the medications directly to patients' homes, while also providing basic health check-up services during the same visit. This approach is expected to reduce the travel burden on patients, increase convenience in receiving services, and promote more comprehensive and sustainable access to healthcare in rural areas.

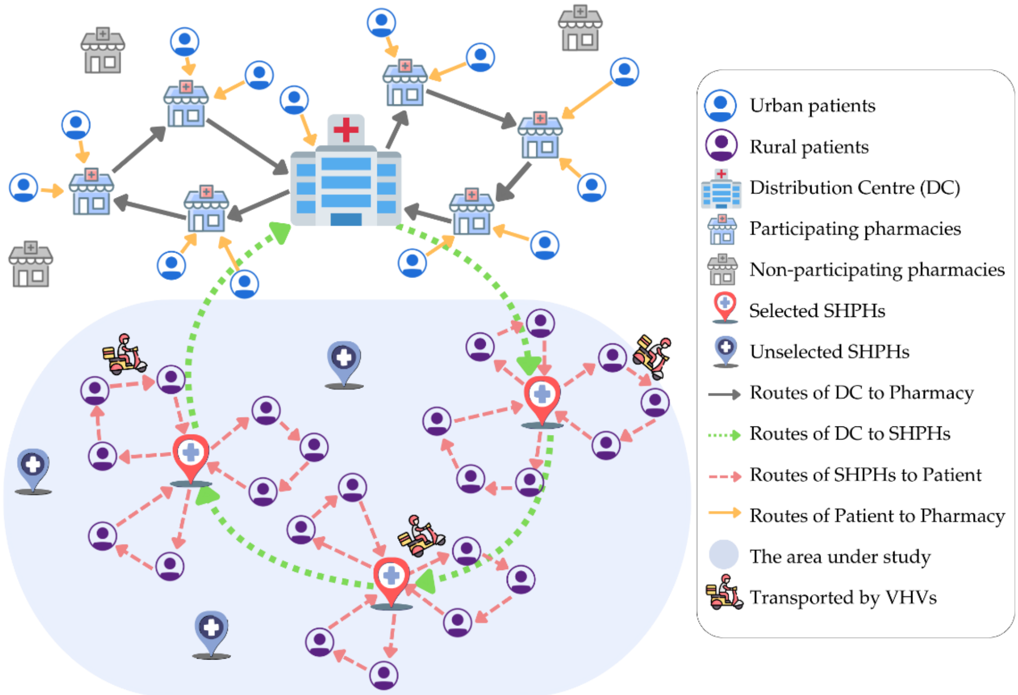

Figure 2. Conceptual Framework of the Research: Location-Allocation Problem and Vehicle Routing Problem.

This research problem is divided into two main levels: (1) the selection of appropriate SHPHs to participate in the program, along with the allocation of patient groups based on their respective catchment areas; and (2) the planning of medication delivery routes and individual patient monitoring using VHVs as the primary service providers. The solving process is conducted using an exact method, implemented through Lingo software to solve the mathematical model formulated as a logistics-based optimization problem.

The study area covers nine subdistricts located in the peri-urban zones of Hat Yai District, Songkhla Province: Khu Tao, Nam Noi, Tha Kham, Thung Yai, Chalung, Thung Tam Sao, Khuan Lang, Ban Phru, and Phatong. One SHPH was designated as a representative unit for each subdistrict. The target group comprises patients diagnosed with hypertension whose residential locations are fully identifiable (100%). These patients have a prevalence rate of 60–70% and exhibit mild symptoms, making them suitable for home-based monitoring by VHVs. Data from the nine subdistricts revealed a total of 58 patients. The primary objectives of the model are to identify appropriate SHPHs, allocate patients to the designated service units, and determine the most efficient medication delivery routes to ensure comprehensive home-based healthcare access while minimizing supply chain costs. The model operates under the following assumptions:

- **Equal Participation Cost:** Each primary healthcare unit (SHPH) incurs an equal fixed cost for participating in the program.
- **Uniform Patient Demand:** For simplification purposes, it is assumed that all patients have an equal level of medication demand, unless otherwise specified in extended scenarios. Although Equation (4) allows for varying service demand per patient, this assumption is adopted in the base case to reduce model complexity.
- **Daily Service Operation:** All delivery and healthcare service operations conducted by village health volunteers (VHVs) are assumed to be completed daily within a single planning period.
- **Motorcycle Accessibility:** Each VHV is assumed to have access to at least one motorcycle for use in delivering medication and providing home healthcare services.

2.4 Mathematical modeling of the location-allocation problem for healthcare facility planning

Strategic spatial planning plays a critical role in healthcare logistics, particularly in ensuring equitable and efficient access to services across diverse populations. Among the most established approaches for this purpose is LAP, a mathematical framework used to determine the optimal selection of service facility locations from a predefined set of alternatives. The objective is to maximize service coverage and operational efficiency while adhering to constraints such as distance, accessibility, and facility capacity. LAP models have been extensively applied in logistics, public health planning, and emergency response systems. To illustrate this concept, Figure 3 presents the fundamental structure of the Location-Allocation Problem, which underpins the spatial design of service networks to effectively and equitably meet population needs.

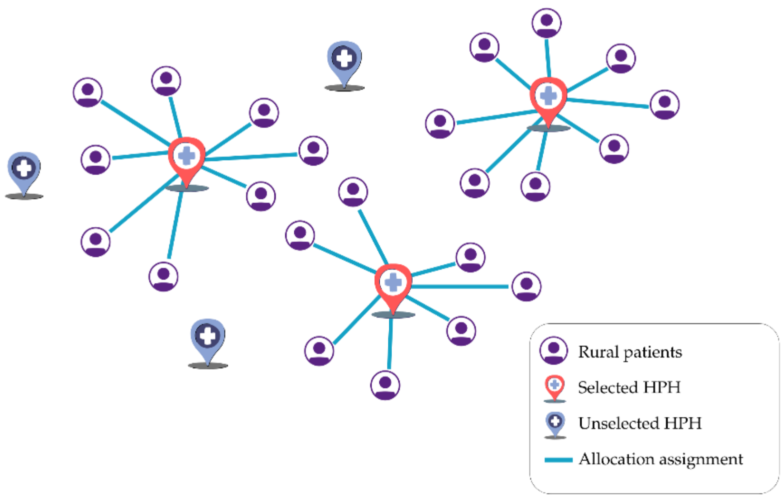

Figure 3. Location-Allocation Problem

The mathematical model representing the problem of selecting SHPHs to participate in the "Taking Medicine Nearby House" project was adapted from the model initially proposed by Perl & Daskin [37], as follows:

Indices

i	Set of potential locations of SHPHs eligible to participate in the "Taking Medicine Nearby House" project
j	Set of locations of patients with hypertension

Parameters

c_{ij}	Transportation cost from SHPH i to hypertensive patient j
f_i	Fixed cost or participation cost of SHPH i in the project
C_i	Capacity of SHPH i to serve patients
D_j	Demand for medication by hypertensive patient j

Decision Variables

$x_i \in \{0,1\}$	A binary variable indicating whether location i is selected as a participating SHPH (1 = selected, 0 = otherwise)
$y_{ij} \in \{0,1\}$	A binary variable indicating whether demand point j is assigned to SHPH i (1 = assigned, 0 = otherwise)

Objective Function

$$\text{Min} \sum_{i \in I} f_i x_i + \sum_{i \in I} \sum_{j \in J} c_{ij} y_{ij} \tag{1}$$

Constraints

$$\sum_{i \in I} y_{ij} = 1, \quad \forall j \in J \tag{2}$$

$$y_{ij} \leq x_i, \quad \forall i \in I, j \in J \tag{3}$$

$$\sum_{j \in J} D_j y_{ij} \leq C_i x_i, \quad \forall i \in I \tag{4}$$

$$x_i \in \{0,1\}, \quad y_{ij} \in \{0,1\}, \quad \forall i \in I, j \in J \tag{5}$$

The objective function in Equation (1) aims to minimize the total system cost, which consists of the participation cost of the primary healthcare facilities (SHPHs) and the transportation cost for delivering medication to patients. Equation (2) ensures that each patient is assigned to only one SHPH. Equation (3) states that a patient can only be assigned to an SHPH that has been selected to participate in the project. Equation (4) represents the capacity constraint of each SHPH in terms of the total amount of healthcare service demand it can accommodate, where each patient may require a different level of service based on individual needs. Finally, Equation (5) defines the decision variables as binary, taking values of either 0 or 1.

2.5 Mathematical modeling of the vehicle routing problem for home-based healthcare services

Efficient route planning is a fundamental component of home-based healthcare logistics, particularly when distributing medical supplies to patients in decentralized communities. VRP provides a mathematical framework for optimizing delivery routes to minimize travel costs while meeting service requirements. In the context of home healthcare in Thailand, the distribution of medicines by SHPHs exemplifies this application. Figure 4 illustrates the core structure of the VRP, emphasizing its role in supporting cost-effective and reliable healthcare delivery beyond conventional clinical settings.

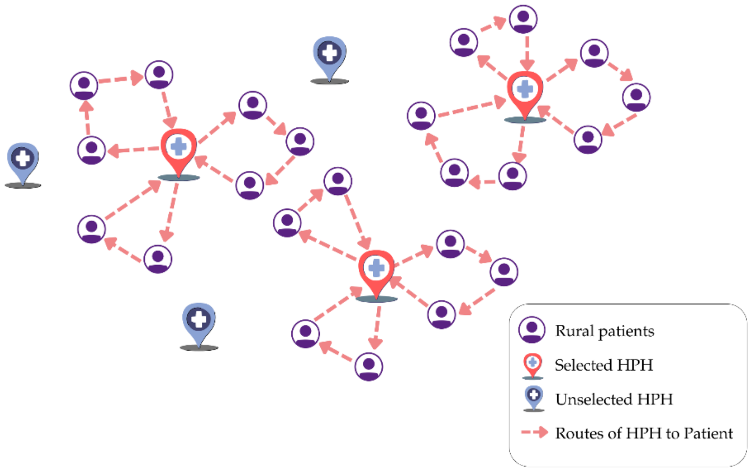

Figure 4. Vehicle Routing Problem

The development of a mathematical model focused on route planning for delivering medication to patients with hypertension under the "Taking Medicine Nearby House" project was carried out by adapting the mathematical model proposed by Kara, Laporte, & Bektas [38].

Indices

i	Set of locations SHPHs eligible to participate in the "Taking Medicine Nearby House" project
j	Set of locations of patients with hypertension

Parameters

c_{ij}	Transportation cost from SHPH i to hypertension patient j
Q	Vehicle capacity
q_j	Quantity of medicine required by the hypertension patient j

Decision Variables

$x_{ij} \in \{0,1\}$	A binary variable indicating whether there is a route from SHPH i to patient j (1 = route exists, 0 = otherwise)
u, m	Auxiliary variables

Objective Function

$$\text{Min} \sum_{i \neq j} c_{ij} x_{ij} \tag{6}$$

Constraints

$$\sum_{j=2}^{n} x_{1j} = m, \tag{7}$$

$$\sum_{i=2}^{n} x_{i1} = m, \tag{8}$$

$$\sum_{j=1,\, j \neq i}^{n} . x_{ij} = 1 \qquad (i=2,\ldots,n), \tag{9}$$

$$\sum_{i=1,\, i \neq j}^{n} x_{ij} = 1 \qquad (j=2,\ldots,n), \tag{10}$$

$$u_i - u_j + Q\,x_{ij} \le Q - q_j \qquad \left(i,j{=}2,\ldots,n;\ i \ne j\right), \tag{11}$$

$$q_i \le u_i \le Q \qquad (i{=}2,\ldots,n), \tag{12}$$

$$x_{ij} = 0 \text{ or } 1 \qquad (i,j{=}\ 1,\ldots,n;\ i \ne j), \tag{13}$$

$$m \ge 1 \text{ and integer} \tag{14}$$

The objective function presented in Equation (6) aims to minimize the total transportation distance. Equations (7) and (8) ensure that each route must start and end at a primary healthcare facility (SHPH). Equations (9) and (10) impose the constraint that each patient must be visited exactly once. Equations (11) and (12) are used to control the total demand on each route, ensuring it does not exceed the vehicle capacity, while also preventing the occurrence of undesired sub-tours. Equation (13) defines the decision variables as binary, taking values of either 0 or 1. Lastly, Equation (14) specifies that the auxiliary variables must be strictly positive real numbers.

The integration of LAP and VRP using exact solution methods represents an appropriate approach for developing an efficient service model within the context of the "Taking Medicine Nearby House" project. This approach can effectively support policy-level decision-making in the equitable and sustainable allocation of healthcare resources to communities and patients.

3. Results and discussion

This research is based on a case study of the "Taking Medicine Nearby House" project conducted in Hat Yai District, Songkhla Province, with a primary focus on patients with chronic conditions and elderly individuals who are unable to travel to collect their medications independently, particularly those diagnosed with hypertension. The study encompasses several key components: the selection of primary healthcare units (SHPHs), the allocation of patients, the planning of medication delivery routes, and the provision of home healthcare services. The proposed model operates under specific constraints, namely that each SHPH may serve a maximum of ten patients, and the initial participation cost for each unit is fixed at 20,000 Baht. Each patient is assumed to require one package of medication. The principal objective of this research is to minimize the total cost of the healthcare service system, with a particular emphasis on transportation expenses. The analysis utilizes actual distance data between the residences of patients and the respective SHPHs, as well as the distances among these healthcare units within the rural areas of Hat Yai. Patient coordinates are derived from official house registration documents, and the distances are computed using the actual road network, processed through ArcGIS software. The results are presented in a distance matrix, as shown in Table 2.

Table 2. Distances between SHPHs and hypertensive patients (kilometers).

Coordinates	P1	P2	P3	P4	P5	P6	...	C57	C58
P1	0.00	30.53	10.32	11.38	12.61	5.64	...	12.42	15.80
P2	30.53	0.00	33.00	34.10	37.10	34.76	...	13.95	14.90
P3	10.32	33.00	0.00	0. 92	4.25	7.32	...	9.47	22.47
P4	11.38	34.10	0. 92	0.00	3.15	8.21	...	10.48	14.77
P5	12.61	37.10	4.25	3.15	0.00	7.76	...	13.72	18.97
P6	5.64	34.76	7.32	8.21	7.76	0.00	...	14.62	18.22
...	...	...	...	...	...	...	...	...	...
C57	12.42	13.95	9.47	10.48	13.72	14.62	...	0.00	5.72
C58	15.80	14.90	22.47	14.77	18.97	18.22	...	5.72	0.00

*P = Point SHPH, C = Hypertensive patients.

After collecting the input data, the mathematical model was transformed into a set of executable commands for processing with the LINGO software. This was done to determine the optimal locations of SHPHs, allocate patients appropriately, and identify delivery routes that comply with the specified constraints. Computational experiments were conducted using LINGO version 19 on a workstation equipped with an AMD Ryzen 5 processor and 32 GB of RAM.

3.1 Selection of SHPH locations participating in the project and patient allocation

To ensure the efficiency of Home Health Care services under the "Taking Medicine Nearby House" project, it is essential to consider both the locations of SHPHs and the spatial distribution of patients. The problem was solved to identify suitable SHPHs and allocate patients to each facility. The program completed the computation in just 2 seconds, and the results are presented in Table 3.

Table 3. Status and Patient Allocation.

Code	Location of SHPHs	Status	Allocated Patients
P1	Khu Tao	Participated	C22, C23, C25, C27, C28, C40, C41, C42, C43, C44
P2	Chalung	Participated	C29, C30, C31, C32, C37, C38, C39, C55,
P3	Thung Yai	Not Participated	-
P4	Thung Tam Sao	Participated	C10, C13, C24, C26, C33, C34, C35, C36, C45, C57
P5	Tha Kham	Not Participated	-
P6	Nam Noi	Not Participated	-
P7	Ban Phru	Participated	C11, C12, C14, C16, C17, C18, C19, C20, C21, C51
P8	Phatong	Participated	C1, C2, C3, C4, C5, C6, C7, C8, C9, C15
P9	Khuan Lang	Participated	C46, C47, C48, C49, C50, C52, C53, C54, C56, C58
			Total Cost 122,196.50 Bath

*P = Point SHPH, C = Hypertensive patients.

From testing the total number of SHPHs across 9 subdistricts and 58 hypertensive patients participating in the project, it was found that 6 subdistricts were suitable for participation. The allocation of patients in each subdistrict is as follows: Khu Tao Subdistrict had 10 patients, Chalung Subdistrict had 8 patients, Thung Tam Sao Subdistrict had 10 patients, Ban Phru Subdistrict had 10 patients, Phatong Subdistrict had 10 patients, and Khuan Lang Subdistrict had 10 patients. The total cost was 122,196.50 THB.

3.2 Transportation routing

Following the location selection of the SHPHs, transportation routes for medicine delivery by VHVs were systematically designed. Transportation costs were calculated based on actual travel distances, using a standardized rate of 36.29 THB per kilometer. This rate includes estimated vehicle-related expenses such as depreciation, labor, fuel, and maintenance costs. Specifically, the depreciation cost was based on a standard value of 60,000 THB for a 110cc motorcycle, assuming a useful life of five years. Using the geographic coordinates of the selected SHPHs and the assigned patient residences, described in Section 3.1, the optimization model was employed to generate cost-effective travel routes for each service area. These routes were designed to minimize the total transportation cost while ensuring complete delivery coverage. The results of route optimization are summarized in Table 4.

Table 4. Transportation Routing Results.

Code	Location of SHPHs	Transportation Order	Computation Time (min: sec)	Cost (THB)
P1	Khu Tao	P1-C28-C23-C22-C25-C27-C41-C42-C44-C43-C40-P1	00.02	115.28
P2	Chalung	P2-C55-C29-C39-C32-C31-C30-C38-C37-P2	00.05	310.03
P4	Thung Tam Sao	P4-C10-C13-C57-C45-C24-C26-C36-C35-C34-C33-P4	00.03	222.95
P7	Ban Phru	P7-C17-C20-C12-C21-C16-C18-C11-C19-C14-C51-P7	00.01	105.90
P8	Phatong	P8-C15-C9-C6-C1-C8-C5-C7-C3-C4-C2-P8	02.39	128.94
P9	Khuan Lang	P9-C50-C46-C48-C49-C53-C54-C58-C56-C47-C52-P9	00.01	69.76
			Total Cost	**952.87**

*P = Point SHPH, C = Hypertensive patients.

Table 4 illustrates the results of medicine distribution routing and transportation costs for the six SHPHs, namely in the subdistricts of Khu Tao, Chalung, Thung Tam Sao, Ban Phru, Phatong, and Kuan Lang, which provide home healthcare services, with a total transportation cost of 952.87 THB. Therefore, when including the costs of selecting the participating SHPH locations, patient allocation, and transportation route planning, the total cost amounts to 123,149.37 THB.

3.3 Sensitivity testing of model parameters

To evaluate the robustness of the model, a sensitivity analysis was conducted by varying key parameters, consisting of the fixed cost of facility participation (f_i), the service capacity of Sub-district Health Promoting Hospitals (SHPHs) (C_i), and patient demand (D_j). For the fixed cost (f_i), the base value was set at 20,000 THB for all facilities. Three scenarios were examined: (1) a uniform reduction to 10,000 THB, (2) a uniform increase to 30,000 THB, and (3) random values assigned to each facility within the range of 10,000 to 30,000 THB. This analysis aimed to assess whether increased investment in establishing service points would remain cost-effective and how such changes would influence the selection of SHPHs.

Regarding service capacity (C_i), the current setup allows each of the 9 facilities to accommodate a maximum of 10 patients, serving a total of 58 hypertensive patients. Three scenarios were evaluated: (1) reducing the maximum capacity to 7 patients per facility, (2) increasing it to 20 patients, and (3) randomly assigning capacities between 7 and 20 patients. These scenarios were analyzed to observe the impact of capacity variation on patient allocation and to determine whether such changes would affect the feasibility of serving all patients. For patient demand (D_j), while the baseline scenario assumes a constant demand of one unit of medication per person (i.e., one sachet of medication), two alternative cases are considered: (1) an increase in the number of units per person, and (2) a randomized demand ranging from 1 to 3 units, depending on the severity of each patient. Specifically, mild cases require 1 unit, chronic conditions require 2 units, and patients with multiple conditions require 3 units. These scenarios are intended to evaluate how variations in resource demand impact overall patient allocation and associated costs.

Notably, the transportation cost parameter (c_{ij}) is not modified in this analysis, as it is calculated based on the actual distance between each community health center (SHPH) and the patient's residence. The cost per kilometer is derived from empirical data specific to the study area, rendering this parameter a fixed input that reliably reflects the real-world context of healthcare service delivery. The case scenarios described above are presented in Table 5. Subsequently, the data were processed using the LINGO program. The results of the analysis for each scenario are summarized in Table 6, with Case 1 representing the baseline scenario.

Table 5. Case Scenarios for Sensitivity Analysis.

Case No.	Case Code	Fixed Cost (THB)	Capacity (Patients/SHPH)	Demand (Units/Person)	Remarks
1	Base	20,000	10	1	Baseline scenario
2	FC-1	10,000	10	1	Reduced fixed cost
3	FC-2	30,000	10	1	Increased fixed cost
4	FC-3	10,000–30,000	10	1	Randomized fixed cost
5	CAP-1	20,000	7	1	Reduced SHPH capacity
6	CAP-2	20,000	20	1	Increased SHPH capacity
7	CAP-3	20,000	7–20	1	Randomized SHPH capacity
8	DEM-1	20,000	20	3	Increased medication demand
9	DEM-2	20,000	20	1–3	Randomized medication demand
10	COMB-1	10,000–30,000	7–20	1–3	Combined randomized scenario

Table 6. Analysis Results of Case Scenarios for Sensitivity Analysis

Case No.	Case Code	Number of SHPHs Opened	Selected SHPHs	Number of Patients Allocated	Total SHPH Participation Cost (THB)	Runtime (seconds)
1	Base	6	P1, P2, P4, P7, P8, P9	58	122,196.50	0.38
2	FC-1	6	P1, P2, P3, P7, P8, P9	58	62,196.53	0.55
3	FC-2	6	P1, P2, P3, P7, P8, P9	58	182,196.50	0.41
4	FC-3	6	P1, P2, P3, P5, P7, P9	58	107,089.20	0.19
5	CAP-1	9	P1, P2, P3, P4, P5, P6, P7, P8, P9	58	182,579.90	0.16
6	CAP-2	3	P6, P7, P9	58	62,350.60	0.80
7	CAP-3	4	P3, P7, P8, P9	58	82,355.76	0.94
8	DEM-1	9	P1, P2, P3, P4, P5, P6, P7, P8, P9	58	188,102.00	0.17
9	DEM-2	6	P1, P2, P5, P7, P8, P9	58	124,388.80	0.61
10	COMB-1	9	P1, P2, P3, P4, P5, P6, P7, P8, P9	58	193,734.40	0.12

To assess the robustness of the proposed model under varying conditions, Table 6 presents how these factors impact total cost, facility utilization, and patient allocation. Adjusting the SHPH participation cost directly influenced total expenditure. Reducing the fixed cost to 10,000 THB (Case 2) lowered the total cost to 62,196.53 THB, while all 58 patients were successfully allocated. Increasing it to 30,000 THB (Case 3) raised costs significantly to 182,196.50 THB. A randomized cost between 10,000–30,000 THB (Case 4) resulted in a moderate cost of 107,089.20 THB. These results highlight that lowering fixed costs can improve budget efficiency without affecting service coverage. Changes in SHPH capacity also had notable effects, namely, limiting capacity to 7 patients (Case 5) requiring all 9 facilities, raising the total cost to 182,579.90 THB. Increasing capacity to 20 patients (Case 6) reduced the need to only 3 facilities and cut costs to 62,350.60 THB— the lowest among all cases. Random capacity between 7–20 patients (Case 7) used 4 SHPHs, with a moderate cost of 82,355.76 THB. Higher capacity boosts operational efficiency. Increasing demand to 3 units per patient (Case 8) led to the use of all SHPHs and a total cost of 188,102.00 THB. Randomized demand between 1–3 units

(Case 9) required 6 facilities and cost 124,388.80 THB. The model adapts well to varied demand levels, though higher or more variable demand increases the cost. Randomizing all three parameters simultaneously required all 9 facilities and yielded the highest cost of 193,734.40 THB. Despite the complexity, the runtime was just 0.12 seconds, indicating high computational efficiency. Across all scenarios, the model consistently allocated all 58 patients, demonstrating flexibility and robustness. However, fixed costs and service capacity were the most influential in determining total cost and facility requirements. These insights can help guide policymakers in optimizing resource allocation and budgeting under varying conditions.

3.4 Discussion

A review of the existing literature on HHC logistics reveals that most studies have primarily focused on improving operational efficiency through routing and scheduling optimization. Various mathematical and algorithmic techniques have been employed to address the VRP and its derivatives. For instance, van Montfort et al. (2024), Phonin et al. (2025), and Atta et al. (2025) emphasized optimizing task allocation, reducing service time, and aligning caregiver assignments with routing efficiency. However, these studies have not incorporated the structure of community-based health systems or considered the socio-spatial contexts of developing countries in their models. The present study introduces a novel approach by integrating both strategic and operational planning levels through the combination of LAP and VRP. The objective is to enhance healthcare access for patients with hypertension and limited mobility in Hat Yai District, Thailand. This differs from prior work such as that of Suwatcharachaitiwong et al. [4], which focused on hybrid delivery models (home delivery and self-collection) without embedding actual community-based primary healthcare infrastructure into the optimization framework. Importantly, this study is the first to explicitly incorporate Subdistrict Health Promoting Hospitals (SHPH) and Village Health Volunteers (VHV)—key components of Thailand's primary healthcare system—into the model. In contrast, although works by Kordi et al. [10], Abdul Nasir and Kuo [11], and Shi et al. [24] addressed flexibility, uncertainty, and cost efficiency, they did not systematically reference local health delivery systems or adapt their models to community-specific infrastructures. In terms of methodology, this research utilizes exact optimization via LINGO in conjunction with Geographic Information Systems (GIS), enabling spatially grounded analysis suitable for real-world community-level planning. This contrasts with many studies that rely solely on mathematical algorithms such as MOVNS, genetic algorithms, or MILP, often tested on generated data, which may not be directly applicable in field settings. For example, while Paradiso et al. [31], Salavati-Khoshghalb et al. [32], and Balti & Jemai [34] proposed advanced techniques, their models are more aligned with urban or industrial logistics rather than healthcare delivery in rural or community contexts. Furthermore, the use of real patient data and authentic community health structures enhances the validity and applicability of the proposed model for local policy-making. This sets the study apart from much of the literature, which tends to rely on theoretical simulations. Consequently, the findings from this research offer a practical framework for proactive, community-based healthcare service planning in Thailand. They could be adapted to similar settings across Southeast Asia that share comparable public health infrastructures.

4. Conclusions

This study aims to design a logistics system that supports home healthcare services under the "Taking Medicine Nearby House Project" in the Hat Yai district, Songkhla province. The focus is on analyzing and planning various aspects, including the selection of suitable primary healthcare units (SHPHs), the allocation of chronic disease patients who are unable to travel for healthcare services, and the development of efficient medication delivery routes and home healthcare services. The analysis process utilizes a mathematical model combined with Geographic Information System (GIS) data to assess the actual distances on the road network, and the processing is conducted using the LINGO program. This approach facilitates the determination of optimal service point locations and the strategic distribution of resources in alignment with both service capacity constraints and the geographical characteristics of the target area. The analysis revealed that the application of the LAP model resulted in a total cost of 122,196.50 THB, while the VRP model produced an average service cost of 952.87 THB per delivery. When combined, the total cost of implementing both models amounted to 123,149.37 THB. Based on the model's output, six out of nine SHPHs were selected to serve as distribution centers. These included Khu Tao, Chalung, Thung Tam Sao, Ban Phru, Phatong, and Khuan Lang.

A total of 58 patients were successfully assigned to these SHPHs without exceeding the individual capacity limitations of any unit, thereby ensuring operational feasibility and balanced workload distribution. The resource allocation and route planning approach used in this research demonstrates the potential to reduce logistics costs in the system, especially transportation costs, which are a critical component of the Home Healthcare system. In conclusion, the application of logistics techniques combined with mathematical models and GIS systems has the potential to enhance the efficiency of primary healthcare service management in the Home Healthcare model. It can be applied to logistics planning for other public health projects in the future.

The implementation of the "Taking Medicine Nearby House" initiative, through the application of Location-Allocation and Vehicle Routing models, provides managerial insight into precise planning for selecting service points and optimizing medication distribution routes. This approach considers both the capacity constraints of individual healthcare units and the geographical characteristics of the target area. Such an integrated strategy enables a more balanced distribution of workloads and contributes to reducing overall system costs—particularly transportation expenses, which are a major component of home healthcare services. It offers a practical and actionable tool to support strategic decision-making, resource planning, and the design of more efficient community-level health service systems. This method proves especially valuable in delivering care to target populations with mobility limitations, such as chronically ill patients and the elderly. It is also adaptable to other public health initiatives, including vaccine distribution and the delivery of medical supplies to remote or underserved areas. In addition to enhancing operational efficiency, the model promotes equity in healthcare access and supports the development of sustainable health systems under resource and budget constraints. The approach aligns with Thailand's national health policy, which emphasizes the delivery of safe, high-quality healthcare services while reducing congestion, disparities, waiting times, and financial burdens [39]. This policy, developed by the National Health Security Office (NHSO) in collaboration with the Ministry of Public Health and a network of service providers—including VHVs, SHPHs, community hospitals, and general hospitals—offers a solid foundation for strengthening primary healthcare delivery nationwide. In this context, the model contributes not only technical solutions but also meaningful managerial insight for improving healthcare systems in a locally responsive and scalable manner.

The suggestion for improving the problem-solving model, based on the characteristics of issues related to both the selection of healthcare service locations and the planning of medication delivery and home services, highlights the necessity of developing a mathematical model that can appropriately integrate both aspects. This model is known as LRP, which presents a potential approach for designing healthcare systems that are both efficient and cost-effective. For smaller-scale case studies, such as those involving a limited number of service units and patients, the use of exact methods can still provide accurate results within an acceptable timeframe. However, when the problem size increases, such as in cases involving 9 service units and up to 157 patients, it was found that processing with the LINGO program required over 100 hours and could not provide a solution within the constrained time limit. Therefore, to enhance the efficiency of solving the problem under time constraints, it is recommended to consider the use of answer approximation techniques, such as Heuristics and Metaheuristics. These methods can significantly reduce computation time while providing practically acceptable results. Furthermore, the mathematical model should be improved to better reflect real-world situations by considering resource constraints, the service capacity of each healthcare unit, as well as geographic factors and travel characteristics specific to each area. This will ensure that the problem-solving approach is appropriate, can be practically applied, and supports strategic decision-making in planning the logistics system for Home Healthcare services effectively in the future.

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