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Optimization of Mobile-Integrated Services: Insights from a Healthcare Use Case

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Abstract

Mobile-integrated service delivery models are emerging as innovative alternatives to traditional centralized models. These models are applied across various service sectors. Due to their significant benefits and growing demand, most existing literature and practical implementations focus on healthcare applications. Their advantages have been demonstrated in several studies. Nevertheless, the literature lacks studies that examine these models from an operations research perspective. Therefore, this study is among the first to describe the mobile-integrated service delivery model through the lens of operations research. It compares the traditional centralized location-based service delivery model with the mobile-integrated alternative and highlights key efficiency-related challenges. Several delivery strategies are discussed, and an optimization model is applied to one of them, focusing on routing. An empirical study is conducted using the case of coronary heart disease (CHD) examinations. In CHD diagnosis, a preliminary consultation determines whether three tests, Complete Blood Count (CBC), Electrocardiogram (ECG), and Computed Tomography (CT), are required. The sequence of these examinations is arbitrary. The results are then sent to a consultant for evaluation. The resulting routes by diagnostic type, demonstrate the model's ability to assign all patients efficiently while minimizing total travel distance. However, the results also reveal overlapping service visits due to the absence of integrated scheduling, highlighting a critical area for further development. This setup illustrates the complexity of the problem and the need for scheduling to avoid service overlap. Several extensions are proposed to advance this topic toward real impact on practice.

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1. Introduction

The healthcare industry has been experiencing a cultural and technological shift thanks to the emergence of digital health [1], [2], [3]. This significant change is transforming the traditional doctor-patient relationship into models that use technologies [4]. For these advancements to be introduced appropriately in the clinical sector, the participation of clinicians and the integration of technology for real-time data monitoring and responsiveness are keys [5], [6]. An interesting view of this switch can be found in the drone-based diagnostic approach, facilitating direct results in remote locations and removing unnecessary delays considering the sample processing [7]. Mobile integrated healthcare programs help reduce trips to the emergency room, improve how patients feel and recover, and help cover the gaps that often exist in traditional healthcare systems [8]. It also helped better use healthcare resources during the COVID-19 pandemic and brought emergency care teams and public health systems closer [9]. In times of crisis, such as floods, MIH providers have proven to be highly adaptable, helping people stay connected to essential care and support when traditional systems are disrupted [10], [11].

At the organizational level, studies like the one on France's national blood collection network show how important it is to improve staff planning and appointment scheduling. These improvements help reduce donor waiting times and enhance the quality of service at both permanent centers and mobile collection units [12]. Significant public health projects have shown how well logistics can work, and intelligent routing algorithms have helped mobile clinics deliver COVID-19 vaccines efficiently to over 47,000 long-term care facilities [13]. Similarly, mobile health teams improved vaccination rates by finding people who had missed follow-up appointments and helping remove obstacles to getting vaccinated in rural areas [14]. Similarly, in the case of chemotherapy, mobile services can play a pivotal role in the delivery of care, and such decisions can be taken through an optimization model [15].

The increasing adoption of mobile medical services proves the pressing need for technology-driven models surpassing traditional healthcare delivery's limitations [16]. As healthcare systems face growing pressures to provide faster and more accessible care, the integration of optimization strategies becomes essential [17]. This work aims to investigate how mobile healthcare delivery can be improved by applying such strategies. The study contributes to developing more efficient patient-centered healthcare solutions by bridging theoretical frameworks with real-world challenges.

The approach proposed in this paper aligns with the principles of Industry 5.0, which emphasizes designing systems that are not only technologically advanced but also human-centric and sustainable [18]. In healthcare, this shift supports models like mobile-integrated services. Unlike Industry 4.0, which focused primarily on automation and data exchange, Industry 5.0 brings people back into the loop by promoting collaboration between humans and intelligent systems [19].

The paper begins by reviewing existing work on mobile-integrated healthcare models, followed by the formulation of an optimization framework designed to improve service delivery. It then presents and analyzes the results of the proposed approach, highlighting key performance metrics. The discussion addresses the implications and limitations of the model, with concluding remarks that outline key insights and directions for future research.

2. Literature Review

A review of the current literature in Table 1 reveals that while several studies have explored mobile healthcare delivery in diverse contexts, such as NCD (Nucleic acid amplification technologies) care [20], mass casualty response [21], stroke intervention pathways [22], and pandemic-related disruptions [23], these reviews primarily focus on system components, diagnostic technologies, and broad public health implications. However, they lack comprehensive systems support, adequate analytics or simulation capability, or optimization-based modelling methods. This article discusses rectifying these deficiencies by combining mathematical and qualitative methods to raise productivity, redesign routes, or make real-time decisions for on-the-job mobile healthcare systems.

Table 1. Review papers

Review Paper	Focus
[20]	Ultrafast diagnostics, point-of-care testing.
[21]	MCC (Mass Casualty Centers)
[22]	Critically reviews models for stroke care
[23]	Impact of COVID-19 on people with diabetes and other

1.1. Mathematical Approach

The potential of mobile-integrated healthcare to close gaps in access to care has been explored through various service models and technologies, as shown in Table 2. The role of mobile clinics in reaching underserved rural communities was highlighted in a time-motion and cost analysis, where it was revealed that services could be adjusted to meet the specific needs of populations, such as rural residents and people experiencing homelessness, while maintaining cost-effectiveness [24]. Public and practitioner views on mobile stroke units were examined in the UK, where support for the model was expressed. However, concerns were raised regarding staffing limitations and integration with existing systems [25]. To address the logistical challenges in mobile healthcare delivery, machine learning was applied to improve route optimization and scheduling for mobile medical units, and it was demonstrated that service coverage and operational efficiency could be significantly enhanced in rural regions [26]. Long-term planning for mobile visits was addressed through a sigmoidal demand model, where service allocation was recommended to consider both present and future uptake potential, especially in preventive care settings [27].

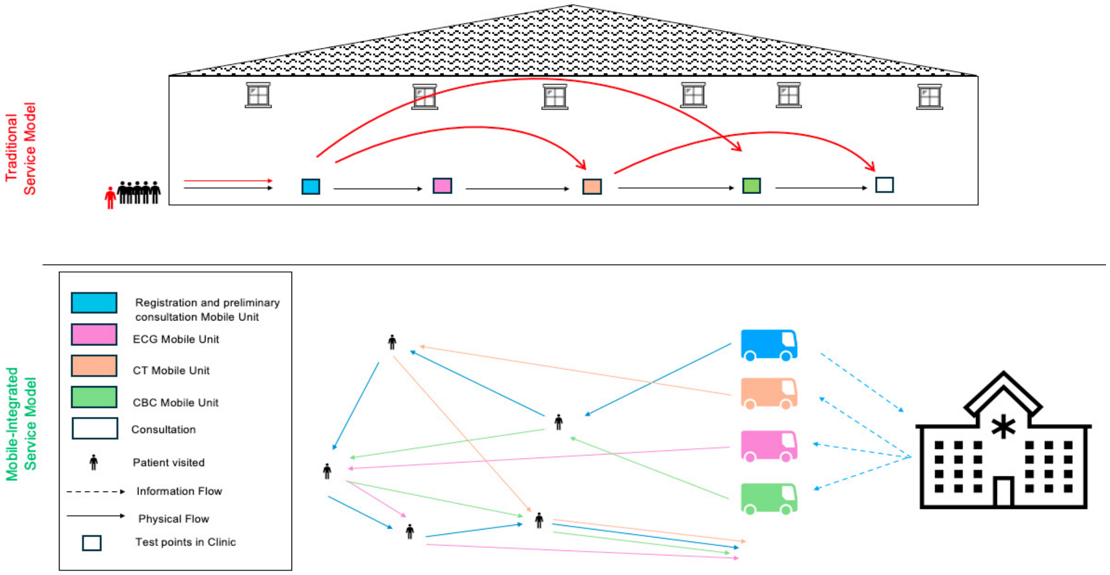

Fig. 1. Traditional vs. Mobile integrated healthcare services delivery models

Flexibility under uncertainty was further addressed through a robust optimization model that integrated both scheduled and walk-in patients, and mobile unit placement strategies were proposed to maximize effectiveness under variable conditions [28]. Vaccine delivery was also studied using a multi-period stochastic model designed to improve how mobile clinics are sent out over time in low, and middle income countries, while considering issues like changing demand and limited road access [29].

Table 2. Comparison with related works

Study	Mathematical Approach	Focus
[29]	Mixed Integer Programming + Multi-period Stochastic Optimization	Vaccine outreach
[28]	Integer Linear Programming + Robust Optimization (Benders Decomposition)	Rural primary care (Germany)
[30]	Network Flow Model + Scheduling	COVID-19 vaccine (U.S.)
[27]	Sigmoidal Optimization	Preventative care
[26]	Heuristic VRP	General rural healthcare access (India)
[24]	Cost Analysis	Rural healthcare access and staffing efficiency
This paper	VRP of Mobile Integrated Healthcare Services Delivery	Diagnostic examinations

2.1 Qualitative approaches

During the COVID-19 pandemic, innovation in mobile diagnostics was accelerated, and a fully automated mobile lab capable of on-site specimen collection, nucleic acid testing, and reporting was developed to support rapid response in outbreak settings [31]. A mobile RT-PCR lab was also designed and deployed in remote parts of Australia, where its performance was validated under field conditions, and its adaptability to shifting testing demands was confirmed [32].

Finally, the importance of standardized procedures in large-scale sampling was emphasized using a mobile biosafety-level lab platform, which was shown to improve the consistency and quality of pre-analytical processes in epidemiologic and environmental health studies [33]. Together, these studies demonstrate how mobile healthcare delivery can be supported through modelling, technology, and field-based solutions to improve accessibility, flexibility, and operational resilience.

3. Problem Description

Figure 1 compares two healthcare delivery models. The top half illustrates the traditional service model, where patients must travel to a fixed clinic and proceed through multiple care stages. In this system, users often form clusters, leading to congestion and long waiting times at each stage of care. These delays can result in inefficient service delivery and potentially worsened health outcomes, particularly in areas with high patient volumes or limited medical staff. This problem was based on a paper focusing on scheduling [34]. The difference here is that the problem is taken outside of the hospital to see if it could have a different reaction towards it.

In contrast, the bottom half of the diagram presents the Mobile-Integrated Healthcare (MIH) model, which is the foundation of this project. In this approach, mobile service units are dispatched from a central clinic or depot to provide care directly in the field, visiting different patient locations. After delivering the initial round of care, medical data is sent back to the central clinic, where decisions are made about which patients require which vehicle service.

One of the initial ideas to solve this problem was to separate the stages per day as shown in Figure 2. In the sense where each vehicle service would have a day where it is assigned to its different patients. This could be practical in nonurgent cases, whereas patients wouldn't have to wait for the different vehicles to come and would know the timing it passes by. However, its downside is that it has a longer lead time compared to if it was done in one day.

The final way focused on for this project is to optimize the routing of mobile healthcare units in two stages as shown on Figure 3. In the first stage, units visit community points for registration and preliminary consultation. The collected data is then sent to the clinic and analyzed. In the second stage, units are sent to deliver service care to patients who need it, which is the stage we are going to focus on.

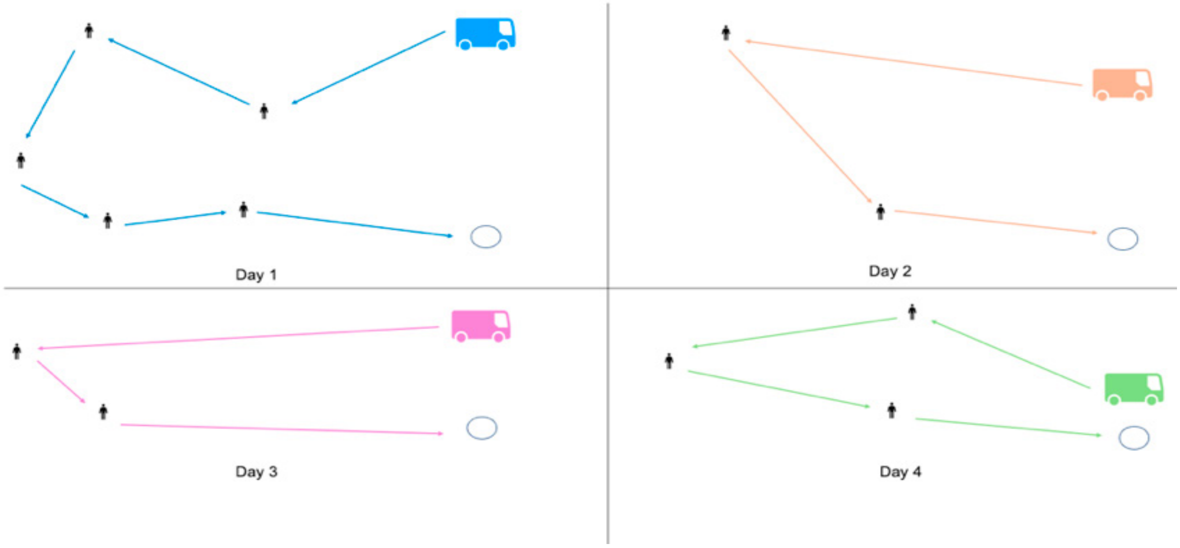

Fig. 2. Daily route separation strategy for patient visits by service vehicles

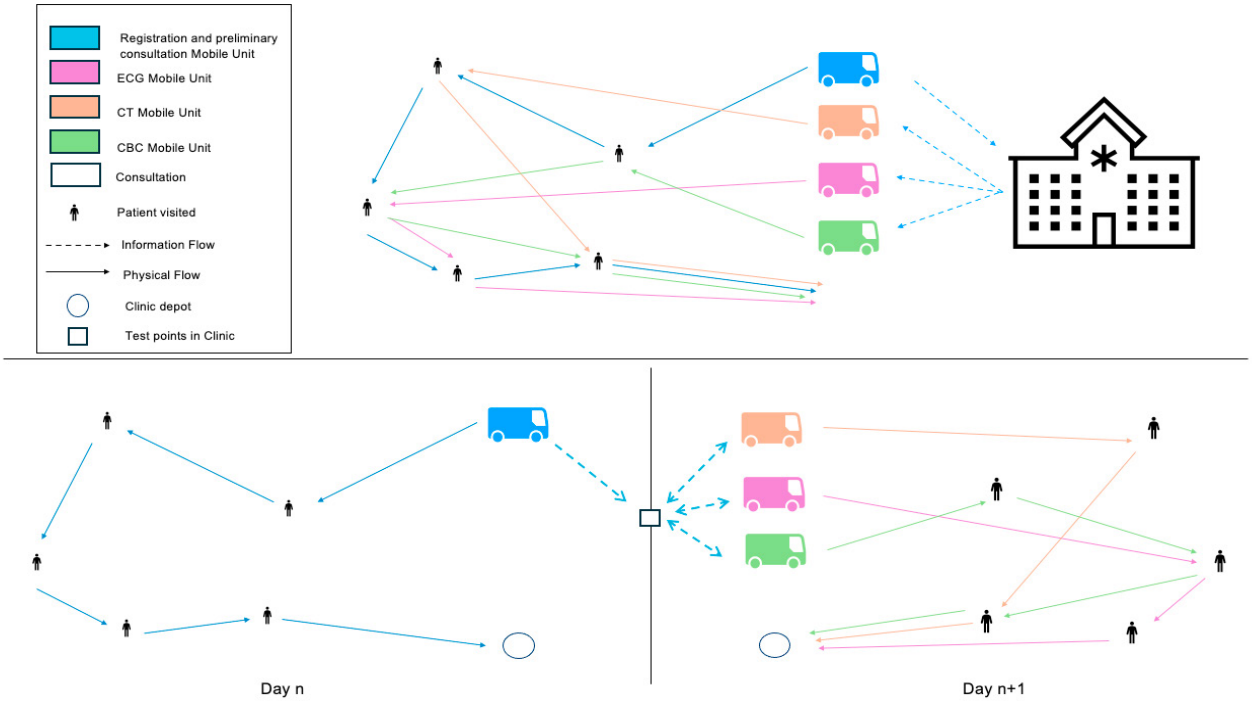

Fig. 3. The proposed two-stage routing framework for mobile healthcare unit

3.1 Mathematical Model

Sets

N: All nodes including depot and patient locations {0,1,2,...,n}

V: Set of Mobile units {1,...,k}

Parameters

d_{ij}: Traveling distance between node i and j

y_i^k: ∈{0,1}, such as $y_i^k = 1$ if Vehicle k travels to node i and, 0 otherwise.

n_k: Number of each location visited depot included

N: All nodes including depot and patient locations {0,1,2,...,n}

V: Set of Mobile units {1,...,k}

Decision Variables

$x_{ij}^k \in \{0,1\}$, such as $x_{ij}^k = 1$ if Vehicle k travels from node i to j, and 0 otherwise.

u_i^k: Continuous variable representing the order of visit at node i, used in the MTZ constraints to prevent subtours. This variable is only defined for nodes i≠0 with 0 being the starting node

Formulation of Objective function: Distance minimization

$$min \sum_{k\in V} \sum_{i\in N} \sum_{j\in N, j\neq i} d_{ij} \cdot x_{ij}^k \quad (1)$$

Constraints

$$\sum_{i\in N, i\neq j} x_{ij}^k = y_j^k \quad \forall k \in V \text{ and } j \in N/\{0\}$$

$$\sum_{j\in N, i\neq j} x_{ji}^k = y_i^k \quad \forall k \in V \text{ and } i \in N/\{0\} \quad (2)$$

$$\sum_{\mathbf{j}\in \mathbf{N}, j\neq 0} x_{0j}^k = 1, \quad \sum_{\mathbf{i}\in \mathbf{N}, i\neq 0} x_{i0}^k = 1, \quad \forall k \in V \quad (3)$$

$$u_i^k - u_j^k + (n_k - 1)\, x_{ij}^k \leq n_k - 2 \quad (4)$$

$$\forall\, i, j \in N, i \neq j \text{ and } k \in V$$

$$1 \leq u_i^k \leq n_k - 1 \quad \forall i \in N,\, i \neq 0 \text{ and } k \in V \quad (5)$$

$$x_{ij}^k \in \{0,1\}\; u_i^k, y_i^k \geq 0 \quad (6)$$

The objective function (1) is to minimize the total distance traveled by all mobile service units. This is subject to the following constraints: (2) each patient location (node) must be visited exactly once, with one entry and one exit by the required mobile service unit, as well as each unit must begin and end its route at a central depot; (3) subtour elimination is enforced using the Miller–Tucker–Zemlin (MTZ) formulation to prevent the formation of disconnected cycles or isolated subgraphs [35]; (4) the auxiliary flow variables u_i^k, used in the MTZ constraints, are bounded to preserve route continuity; (5) routing decisions are modeled using binary variables indicating whether a unit travels between two specific locations; and (6) all relevant variables are constrained to be non-negative to maintain physical feasibility.

4. Solving Methodology & Results

The vehicle routing problem was formulated and implemented using AIMMS optimization software. After developing the mathematical model to assign mobile healthcare units to patients, the model was encoded and solved within the software. The objective was to minimize the total routing distance while ensuring the appropriate mobile units covered all patient locations.

The resulting routes were visualized using four diagrams showed in Figure 4. The top-left map represents the aggregated routing for all mobile units, while the other three diagrams illustrate the individual routing paths for the Electrocardiogram (ECG), Computed Tomography (CT), and Complete Blood Count (CBC) services in coronary heart disease (CHD) diagnosis. Although the routing solutions effectively minimize travel distances, several overlapping service visits were observed. This is due to the model's exclusive focus on routing, without integrating any time-based scheduling or coordination between units.

Although the routing model was successful, in the sense where each vehicle was assigned to a patient, the problem of scheduling did manifest itself to be an issue no matter the way healthcare is delivered, in or out of the hospital. Without considering service start time processing time, the model was fully focused only on making sure each patient receives the service it needed without caring of the overlap. To partially address this, a manual scheduling was made in Figure 5, however it is not necessarily an optimal one, and of course for bigger models this wouldn't be efficient.

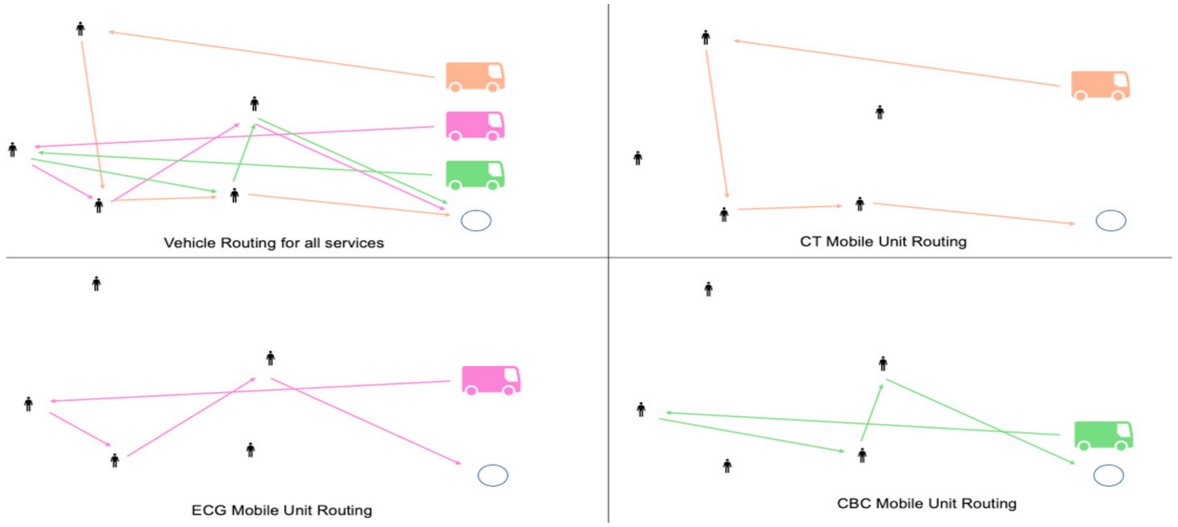

Fig. 4. Routing optimization results

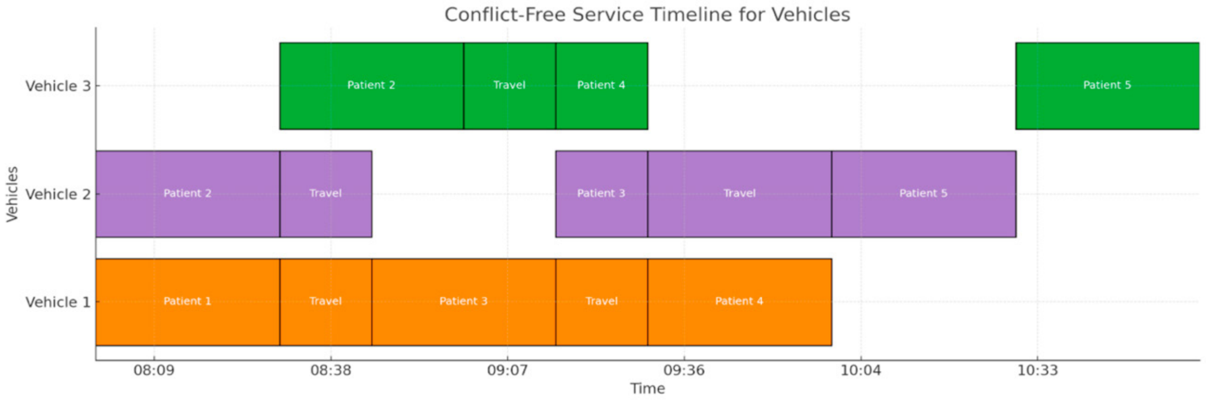

Fig. 5. Illustration of a feasible service schedule

5. Limitations and Future Research

For future research, expanding the model by integrating scheduling optimization directly into the mathematical formulation would be valuable [36]. Introducing service start times and adding precedence or separation constraints between vehicle visits at the same patient site would prevent overlap. Considering uncertainties, such as unexpected delays, cancellations, or emergency reassignments, through robust or stochastic optimization models would make the system more resilient in real-world applications [37]. For the sake of simplicity each service had a mobile vehicle, what could be interesting is to have all the services compiled in one vehicle, specially for bigger scopes, the model should be adjusted to be able to fit. These additions would bridge the gap between theoretical optimization and operational realities in mobile healthcare services.

6. Conclusion

This paper addresses a critical gap in the literature by exploring mobile-integrated healthcare services through an operations research lens. While the growing adoption of such services highlights their practical value, the operational complexity (particularly in routing and scheduling) remains underexplored. The study begins by outlining various strategic approaches to mobile service delivery, highlighting the trade-offs between different configurations. An optimization model focusing on routing was implemented and tested in a case study involving CHD diagnostics. This experimental application not only demonstrates the feasibility of the approach but also reveals persistent challenges, such as overlapping service assignments, which underline the need for integrated scheduling. Compared to heuristic-based models like the reinforcement learning approach used [26], our method delivers a more structured, deterministic optimization with measurable guarantees on route completion and resource allocation. Moreover, the separation of services into individual vehicle routes allows for tailored resource allocation, minimizing idle time and overlaps. In contrast to stochastic models like [28], which focus on flexibility under uncertainty, this model prioritizes deterministic precision in urban and semi-structured environments. Through this illustrative example, the paper offers insight into the intricacies of mobile healthcare delivery and proposes concrete directions for extending the work. These include embedding scheduling mechanisms into the optimization model and accounting for real-world uncertainties. By doing so, future research can help bridge the gap between conceptual planning and effective on-ground deployment. This study serves as a foundational step toward operationalizing mobile-integrated services and improving their efficiency, responsiveness, and practical impact.

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