

Optimizing primary care networks in Guanajuato: planning and allocation of services

Optimización de las redes de atención primaria en Guanajuato: planificación y asignación de servicios

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Recibido: 02-09-2025

Aceptado: 26-09-2025

RESUMEN

Garantizar un acceso equitativo a los servicios de atención primaria en salud requiere un diseño estratégico de las redes de prestación de servicios, lo cual comparte desafíos fundamentales con el diseño de redes de cadena de suministro, incluyendo la localización de instalaciones, la asignación de capacidad y la optimización de la cobertura de servicios. Este estudio propone un modelo bi-objetivo de programación entera mixta para optimizar las decisiones de inversión y ubicación de Unidades de Atención Primaria en Salud (PHUs, por sus siglas en inglés) bajo restricciones presupuestarias. El primer objetivo minimiza la distancia total de viaje para consultas médicas esenciales, mientras que el segundo maximiza la cobertura poblacional de servicios complementarios —nutrición, atención dental, salud mental, análisis clínicos e imagenología—, cada uno con radios de cobertura específicos. Diferentes

tipos de PHUs ofrecen capacidades y carteras de servicios variables, lo que introduce compensaciones explícitas entre accesibilidad, disponibilidad de servicios y costo. El modelo se resuelve utilizando el método epsilon-constraint mejorado (AUGMECON2), lo que permite una exploración eficiente de soluciones Pareto-óptimas. Un estudio de caso en Guanajuato, México, que abarca ocho regiones, 46 municipios, 3.44 millones de puntos de demanda, 515 PHUs existentes y 486 sitios candidatos, demuestra la aplicabilidad del modelo utilizando datos oficiales de demanda, capacidades y costos de inversión actualizados. Los resultados muestran que las regiones urbanas logran una cobertura casi universal de servicios complementarios con presupuestos moderados, mientras que las áreas rurales requieren mayores inversiones para cerrar brechas de servicio, lo que resalta la importancia de una planificación sensible al contexto. Al

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enmarcar la infraestructura sanitaria como una red de servicios en múltiples niveles, el enfoque propuesto ofrece a los tomadores de decisiones una herramienta transparente y basada en datos para evaluar los compromisos entre apertura de instalaciones, expansión de capacidad y cobertura de la demanda. Más allá del sector salud, la metodología es adaptable a

otras redes de servicios públicos que enfrentan recursos limitados y patrones de demanda cambiantes, contribuyendo al campo más amplio del diseño y optimización de redes de suministro.

Palabras clave: modelo bi-objetivo, planeación en salud, localización de instalaciones, atención primaria en salud

ABSTRACT

Ensuring equitable access to primary healthcare services requires strategic design of healthcare delivery networks, which shares fundamental challenges with supply chain network design, including facility location, capacity allocation, and service coverage optimization. This study proposes a bi-objective mixed-integer linear programming model to optimize investment and placement decisions for Primary Healthcare Units (PHUs) under budgetary constraints. The first objective minimizes the total travel distance for essential medical consultations, while the second maximizes population coverage of complementary services—nutrition, dental care, mental health, clinical analysis, and imaging—each with service-specific coverage radii. Different PHU types provide varying capacities and service portfolios, introducing explicit trade-offs between accessibility, service availability, and cost. The model is solved using the improved epsilon-constraint method (AUGMECON2), enabling efficient exploration of Pareto-optimal solutions. A case study in Guanajuato,

Mexico, encompassing eight regions, 46 municipalities, 3.44 million demand points, 515 existing PHUs, and 486 candidate sites, demonstrates the model's applicability using official data on demand, capacities, and updated investment costs. Results reveal that urban regions achieve near-universal complementary-service coverage with moderate budgets, whereas rural areas require higher investments to close service gaps, highlighting the importance of context-sensitive planning. By framing healthcare infrastructure as a multi-tier service supply network, the proposed approach provides decision-makers with a transparent, data-driven tool to evaluate trade-offs between facility opening, capacity expansion, and demand coverage. Beyond healthcare, the methodology is adaptable to other public service networks facing constrained resources and evolving demand patterns, contributing to the broader field of supply chain network design and optimization.

Keywords: bi-objective model, healthcare planning, facility location, primary healthcare services.

INTRODUCTION

Universal access to quality healthcare services is widely recognized as a cornerstone of societal well-being [1]. However, in many developing countries, significant inequalities persist due to uneven resource distribution, limited geographic accessibility, and differences in service quality across healthcare facilities. These systemic gaps, combined with the absence of comprehensive health insurance for large segments of the population, hinder access to essential medical care [2]. In the pursuit of reducing this inequality, institutions have emerged with the important task of attending to individuals without health insurance, providing them access to primary services in situations where economic barriers block access to private services [3]. In the context of Mexico, the Mexican Ministry of Health (Secretaría de Salud, SSA, in Spanish) assumes the most vital role in this commission. As the primary healthcare governmental institution responsible for public health issues, supported by the government's duty to provide essential resources, it manages and supervises the implementation of health policies and initiatives within the country. Its purpose is to provide medical care and preventive services to individuals who could be marginalized from medical attention through its network of Primary Healthcare Units (PHUs) and hospitals [4]. However, the healthcare system in Mexico is complex and comes with its own set of challenges. The current healthcare system in the country reflects the interplay of numerous factors, including how institutions are divided, the limitations on available funds, and the necessity to adjust to the changing needs of the population [5]. In this context, the need for optimizing resource planning and facility positioning emerges as a crucial requirement to ensure that medical care reaches individuals with the greatest need.

In 2020, in the state of Guanajuato, Mexico, the National Institute of Statistics and Geography, (INEGI, *by its acronym in Spanish*) reported that approximately 21% of the population (1.2 million) lack formal health insurance [6]. This data strongly emphasizes the critical importance of addressing these disparities in healthcare access. Therefore, the present study aims to address this challenge through a thorough analysis of the healthcare situation, subsequently presenting an optimization model for the placement of new PHUs. This model incorporates service demand and capacity, providing a comprehensive framework for decision-making. This study proposes a bi-objective mixed-integer linear programming model to improve access to primary healthcare services by optimizing the investment of the PHUs of the SSA. The services provided in these facilities were classified into the main service that corresponds to the basic medical consultation and the complementary services such as nutrition counseling, dental care, mental health, clinical analysis, and imaging. For the primary service, which is available at all PHUs, demand is allocated to capacitated PHUs to minimize the total travel distance from demand points. As for complementary services, which are limited to specific PHUs, the goal is to maximize demand coverage. The problem includes a budget constraint to open new PHUs or upgrade the existing ones to increase the capacity of the main service and the availability of complementary services. This problem is applied to a Case Study based on the State of Guanajuato, Mexico, divided into eight regions. The Pareto set for each region was obtained using the Epsilon-constraint method,

specifically employing an improved version known as the AUGMECON2 methodology [7]. The case study results help measure the potential benefits of using this model in real sceneries.

The field of facility location has grown with a high impact on science in recent decades, especially in the context of healthcare services. A variety of location models have been proposed and tailored to tackle many challenges in the industry and public sectors. A comprehensive compilation of these models has been outlined by [8] and recently [9]. The investigation presented here is closely linked to the healthcare field, which has also seen significant contributions. To achieve a comprehensive understanding of the field, surveys such as those undertaken by [10] and [11] are noteworthy, exploring the diverse domain of healthcare facility localization. However, the roots of this exploration reach back to historical surveys by [12] - [16] which played a key role in deepening the understanding of the intricacies in this field. Furthermore, [17] laid the foundation for contemporary research, presenting an array of multi-objective models and methodologies relevant to facility localization.

The critical task of healthcare facility localization has garnered considerable attention in the research community. The foundational work of [18] addresses the Capacitated Maximal Location Problem (CMLP), maximizing population allocation within coverage radii with capacity limitations. In this lineage, the contributions of [19] and [20] are significant. [21] push the boundaries further, incorporating multiple capacity levels, influencing our approach. A distinct perspective is presented by [22], who contemplates the strategic positioning of drone launch sites for resource distribution. The synergy between location and healthcare has led to new questions. [23] have developed hierarchical models that merge facility localization, allocation, and demand coverage into a unified framework. Simultaneously, authors like [23] - [26] and explore multi-objective and multicriterial models, expanding the range of optimal solutions.

Focusing on Mexican healthcare, a series of studies by [27] offer a comprehensive approach to planning diagnostic services within Mexico's segmented healthcare system, emphasizing cost-effective equipment allocation and patient referrals. In a related context, [28] present a hybrid metaheuristic framework for specialized diagnostic services, delivering cost-effective solutions. [5], [29] and [30] address the critical challenge of optimizing Primary Healthcare unit allocation and minimizing patient travel distances. [31] propose an undisclosed mathematical modeling approach to optimize existing Primary Healthcare Centers, aiding resource allocation and network performance improvement in the face of evolving demographics and limited investments. [32] propose a maximal covering location model with partial coverage and variable radii to optimize the placement of second-level specialized healthcare services in Mexico. [33] explore the efficient deployment of mobile units to enhance healthcare coverage, particularly in low-income areas. These studies provide valuable tools for optimizing healthcare facilities and resource allocation, with potential global applications. However, this study pursues the combination of the Capacitated Facility Location Problem (CFLP) and the Maximal Covering Location Problem (MCLP) to address the localization of primary healthcare centers within the public sector. Our model considers various facility types, each with distinct cost and service implications. Additionally, it proposes

a solution to handle complementary services within facilities with finite capacities. This adaptation builds upon an integration and refinement of established models, providing the potential to generate effective solutions for the complex task of healthcare facility localization within the constraints of limited resources.

The remainder of this paper is organized as follows. Section 2 introduces the problem formulation, describing the bi-objective mixed-integer programming model along with its parameters, decision variables, and constraints. Section 3 presents the solution methodology, detailing the improved epsilon-constraint approach employed to efficiently generate the Pareto frontier. Section 4 describes the case study conducted in the state of Guanajuato, Mexico, including data sources, demand characterization, and network configuration. Section 5 reports the Results and Analysis, discussing trade-offs between accessibility, complementary service coverage, and budget allocation. Finally, Section 6 summarizes the main conclusions and outlines potential directions for future research.

PROBLEM FORMULATION

The following problem is taken up from [5]. However, in this case, the study addresses a bi-objective problem. In the original model, a single objective function was considered while the other was constrained. In the present formulation, two types of services are analyzed. The Main service (MS) corresponds to the outpatient service provided by a physician. The Complementary Services (CS) are other services available in some PHUs such as nutrition counseling, dental care, mental health, clinical analysis, and imaging. Demand for MS must be allocated in the problem to PHUs without exceeding their capacities. In this sense, the objective is to minimize the sum of the travel distance of all the demand. In the case of CS, the objective is to maximize the coverage of demand. To evaluate the coverage, a critical coverage radius is considered for each CS type. In the problem, there are various levels of PHU, as increase the level, additional capacity of the MS and additional CS are available, but the investment cost increases. In the problem is considered the option to upgrade existing PHUs to a higher level but also is considered the option to open new PHUs in candidate site. These decisions are limited by a budget.

For the sake of completeness and a better understanding of the proposed solution method, the integer linear formulation of the problem proposed by [5] is reproduced. The notation, parameters, and variables used in the problem formulation are the following:

Sets:

- | | |
|-------|---|
| M | Set of demand points; $i \in M$. |
| N | Set of existing PHUs and candidate locations to install new PHUs; $j \in N$. |
| N_A | Subset of locations such that a PHU is already installed. |
| N_B | Subset of locations such that a new PHU can be installed. |

K	Set of PHU types; $k \in K$.
$K(j)$	Subset of PHU types to install or upgrade at location $j \in N$.
S	Set of complementary services; $s \in S$.

Parameters:

F^k	Fixed cost of installing the PHU type $k \in K$.
U_j^k	Fixed cost of upgrading the PHU located at $j \in N_A$ to a PHU type $k \in K$.
B	Available budget for installing or upgrading PHUs.
D_{ij}	Distance from demand point $i \in M$ to the PHU located at $j \in N$.
P_i	Demand (number of people) of the main service and the complementary services at point $i \in M$.
C^k	Capacity (number of people) of the PHU type $k \in K$ for providing the main service.
TTD	Upper bound on the total travel distance by the demand for receiving the main service.
R^s	Critical distance of coverage for the complementary service $s \in S$.
T^{ks}	Auxiliary parameter equal to 1 if the complementary service $s \in S$ is provided by the PHU type $k \in K$; and 0, otherwise. This parameter does not appear in the model, but it is used for computing parameters below A_{ij}^{ks} .
A_{ij}^{ks}	Coverage parameter equal to 1 if a PHU type $k \in K(j)$ located at site $j \in N$ covers the demand point $i \in M$ for the complementary service $s \in S$.

Decision variables:

y_j^k	Binary variable equal to 1 if the PHU type $k \in K(j)$ is located at site $j \in N$ and 0, otherwise.
x_{ij}	Binary variable equal to 1 if the demand point $i \in M$ is allocated to the PHU located at $j \in N$ for the main service; and 0, otherwise. $x_{jj} = 1$ represents a facility located at demand point j .
v_i^s	Binary variable equal to 1 if the service $s \in S$ of the demand point $i \in M$ is covered; and 0, otherwise.

Optimization model:

$$\text{Minimize} \quad Z_1 = \sum_{i \in M} \sum_{j \in N} P_i D_{ij} x_{ij} \quad (1)$$

$$\text{Maximize} \quad Z_2 = \sum_{i \in M} \sum_{s \in S} P_i v_i^s \quad (2)$$

$$\text{Subject to} \quad \sum_{j \in N} x_{ij} = 1 \quad i \in M \quad (3)$$

$$\sum_{i \in M} P_i x_{ij} \leq \sum_{k \in K(j)} C^k y_j^k \quad j \in N \quad (4)$$

$$x_{jj} \geq \sum_{i \in M} y_j^k \quad j \in N \quad (5)$$

$$\sum_{k \in K(j)} y_j^k \leq 1 \quad j \in N_A \quad (6)$$

$$\sum_{k \in K(j)} y_j^k = 1 \quad j \in N_B \quad (7)$$

$$v_i^s \leq \sum_{j \in N} \sum_{k \in K(j)} A_{ij}^{ks} y_j^k \quad (8)$$

$$\sum_{j \in N_A} \sum_{k \in K(j)} U_j^k y_j^k + \sum_{j \in N_B} \sum_{k \in K(j)} F^k y_j^k \leq B \quad (9)$$

$$x_{ij} \in \{0,1\} \quad i \in M, j \in N \quad (10)$$

$$y_j^k \in \{0,1\} \quad j \in N, k \in K(j) \quad (11)$$

$$v_i^s \in \{0,1\} \quad i \in M, s \in S \quad (12)$$

The first objective function Eq. (1) aims to minimize the total travel distance of the demand to the PHU for receiving the main service. The second objective function Eq. (2) seeks to maximize the total demand coverage of the complementary services. Constraints Eq. (3) ensure that each demand point is allocated to a single facility for the main service. Constraints Eq. (4) ensure that the total demand allocated to each PHU must not exceed its capacity. Constraints Eq. (5) force to allocate demand to a site where a PHU is located. Constraints Eq. (6) ensure that an existing PHU can be upgraded to another PHU type or can remain its current PHU type. Constraints Eq. (7) allow to open a single PHU type on a candidate site. Constraints Eq. (8) activate the variable v_i^s if a demand point is covered by a complementary service. Constraint Eq. (9) limits the number of PHU to be upgraded and PHUs opened in a candidate's sites according to the budget limit. Finally, the nature of the decision variables is specified by constraints Eq. (10) – Eq. (12)

SOLUTION METHODOLOGY

The previous bi-objective linear integer programming model was solved using the epsilon-constraint methodology for multi-objective optimization. The goal is to find a set of solutions that optimize multiple conflicting objectives simultaneously. This method transforms a multi-objective optimization problem into a series of mono-objective problems by introducing an epsilon parameter and turning one objective into a constraint while optimizing the others. The method found in the Pareto set is the set of solutions in the decision space where no solution is superior to another in all the objectives. These solutions are considered Pareto optimal, as they represent a trade-off between objectives, and there is no way to improve one objective without degrading another.

The AUGMECON method represents an enhancement of the original epsilon-constraint method and is widely recognized for its effectiveness in generating Pareto front representations. In this study, AUGMECON2 [34] was employed, an improvement upon AUGMECON [35] that leverages information from slack variables in each iteration. This enhancement leads to a reduction in computation time by avoiding redundant iterations and optimizing the overall process.

In the introduced problem, the objective function Z_2 was moved to the constraints as is shown in the following model:

$$\text{Minimize} \quad Z_1 - \text{eps} \times \text{Slack} \quad (13)$$

$$\text{Subject to} \quad Z_2 - \text{Slack} = e \quad (14)$$

The new constraint Eq. (14) is equal to a new parameter (e) that represents a minimum bound for the constrained objective function. This parameter is systematically modified to generate different Pareto points. The number of Pareto points increases as the number of different e values are proposed. A new variable (Slack) is created to store the difference between Z_2 and e . Since a higher value of the Slack variable is desirable because it improves the maximization of the covered demand for complementary services, this variable is added to the objective function but is multiplied by a very small value (1×10^{-9}) to not generate conflict with Z_1 . The other constraints of the original model remain equal.

To generate the bound of the new constraint Eq. (14) it is required to find the extreme points of the Pareto set using lexicographic optimization. For the first extreme point, the original model is solved minimizing only Z_1 obtaining as objective value Z_1^+ . Then, the problem is solved by minimizing Z_2 , while adding the following constraint. The objective function value obtained from this problem corresponds to the first extreme point e_1 .

$$Z_1 \geq Z_1^+ \quad (15)$$

The second extreme point is generated similarly, but in this case, Z_2 is firstly minimized and the solution Z_2^+ is included in a new constraint while Z_1 is minimized as follows:

$$Z_1 \leq Z_1^2 \quad (16)$$

With the last problem solved, the second extreme point e_2 is generated. Once the two extreme bounds are generated, $n - 2$ equidistant points are calculated between these two values, to obtain total n Pareto points. In the implementation of this method, some e_t such that $t = 1, 2, \dots, n$ may generate the same Pareto points; therefore, the number of Pareto points is not always n . However, these cases can be omitted to be solved because require unnecessary computing time. To determine if a problem must be solved the following equations are computed:

$$\text{Step} = \frac{e_2 - e_1}{n - 1} \quad (17)$$

$$b = \text{int}(\text{Slack}/\text{Step}) \quad (18)$$

where $\text{int}()$ is the function that returns the integer part of a real number.

CASE STUDY

The addressed bi-objective problem was applied to the case study of the state of Guanajuato, one of the 32 federal entities of Mexico. This territorial unit is divided into 46 municipalities, comparable to counties in the United States, encompassing a total of 12,340 demand points subject to this analysis. Covering an area of 30,606.7 km², the state accounts for approximately 1.6% of Mexico's total landmass, as visually depicted in Figure 1.



FIGURE 1: *A map of the state of Guanajuato along with its demand points.*

The dataset used in this study is available at Mendeley Data. Demand points and population data were obtained from the 2020 Population and Housing Census published by INEGI [6], considering two geographical levels: locality (ITER) and Basic Geo-statistical Area (AGEB). Using the geographic coordinates of each locality, a Euclidean distance matrix was constructed to estimate travel distances between demand points and healthcare facilities [6]. Information on existing PHUs—including their locations, types, and capacities—was collected from the Directorate General of Health Information of the Mexican Ministry of Health [36]. Installation and upgrade costs for PHUs were obtained from the “Resource Models for Planning Health Units” report [37], with values updated to reflect recent economic conditions. These integrated datasets provided the necessary inputs for modeling demand distribution, facility capacities, costs, and distances within the healthcare network.

As depicted in Figure 2, the state is divided into eight regions. The territorial division plays a crucial role in this study, providing the necessary framework for analyzing regional patterns and evaluating the model's impact in various specific geographical areas. Due to the complexity of the problem, solving it

for the entire state of Guanajuato in a single instance is not feasible. Therefore, the decision was made to address the issue regionally. This territorial structure facilitates data collection and analysis, allowing for a deeper understanding of local and regional dynamics. Furthermore, the territorial subdivision is considered essential for the effective administration of policies and services, with its understanding being vital to address specific challenges and facilitate equitable development.

In that context, [Table 1](#) provides a comprehensive overview of demand points, demand quantity, existing PHUs in each region, their capacities for the main service, current utilization rates, and potential candidate sites for PHU installations. Capacity is determined by considering the type of PHU multiplied by the 'basic kernel,' equivalent to the capacity to serve 3,000 inhabitants, a crucial parameter in the analysis. For instance, when examining Region 1, it becomes evident that its capacity to provide primary medical services, specifically medical care, significantly surpasses the current demand. This results in a utilization rate of only 55% of its total capacity, indicating a substantial margin for accommodating more patients, as can be observed in column number 6. Conversely, in contrast, in region 6, the situation is inverted. The demand exceeds the available capacity to serve the population, resulting in a utilization rate of 114%. With these examples, it was observed that one region has greater capacity, while the current capacity of another region is not sufficient to meet the demand.

Furthermore, it is imperative to highlight the identification of candidate sites in each region. The selection of these sites was based on three essential criteria. Firstly, locations were chosen under the criterion that they are not close to existing PHUs, with a minimum distance of 3 km to ensure equitable access. Secondly, preference was given to areas with a minimum population of 500 inhabitants to

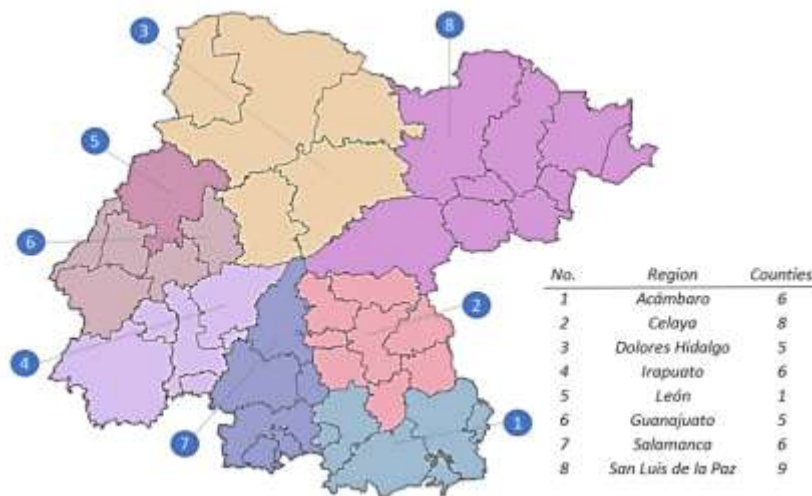


FIGURE 2: *Territorial division in municipalities of the State of Guanajuato.*

Table 1: Regional healthcare and demand data summary.

Region	Demand Points	Demand (inhabitants)	PHUs	Main Service		Candidate Sites
				Capacity (inhabitants)	% of Utilization	
1	650	219,599	64	396,000	55	20
2	1,260	570,838	81	630,000	91	35
3	1,398	365,851	63	429,000	85	100
4	1,303	497,621	69	543,000	92	69
5	988	685,565	62	687,000	100	44
6	980	328,068	47	288,000	114	32
7	963	409,419	58	480,000	85	42
8	1,362	362,808	71	432,000	84	144
Total	8,904	3,439,769	515	3,885,000	89	486

Source: Authors' elaboration based on INEGI (2020) [6] and Secretaría de Salud data [36, 37].

establish an effective population base. Lastly, candidate sites were selected, prioritizing distance from existing medical units, with a specific focus on addressing geographically remote or challenging-access regions. A total of 486 candidate sites were identified throughout the state of Guanajuato. These criteria serve as the foundational pillars of the strategy for locating new healthcare centers, with a strong commitment to maximizing their impact and promoting equity in the provision of medical services.

Table 2 illustrates the number of PHUs with complementary services available in each region, encompassing nutritional counseling (CS1), dental care (CS2), mental health (CS3), clinical tests (CS4), and imaging (CS5). It also incorporates the % demand for a concise overview of both service availability and proportional demand across regions. Notably, the availability of these services varies across different regions. For instance, it is worth noting that the number of CS1, CS2, and CS3 services is consistent across regions, as these services are typically considered foundational in most basic healthcare units. However, services such as clinical analysis and imaging exhibit disparities in their availability within certain healthcare units. Factors influencing this variation include financial resources, local demand, health policies, and hospital management decisions, all of which play a role in determining the presence of these services in a particular hospital or region. Additionally, a correlation is observed between the proportion of demand and the number of healthcare units with complementary services. For example, in region 5, which accounts for 20% of the total demand, it is notable that there is more healthcare units compared to other regions that have a lower percentage of the total demand. The planning and development of healthcare services are intricate and multifaceted endeavors, requiring a delicate balance between the population's needs and the resources at hand.

Table 3 offers an overview of the PHU types and their respective characteristics. The second column provides details on primary service capacity, indicating the number of individuals each facility can permanently serve. Facility type 1 has a capacity of 3,000 inhabitants, and subsequent facility types have

Table 2: Number of complementary services available in each region.

Region	Demand %	Complementary Services				
		CS1	CS2	CS3	CS4	CS5
1	6	10	10	10	5	4
2	17	18	18	18	11	9
3	11	7	7	7	5	5
4	15	11	11	11	9	9
5	20	35	35	35	14	7
6	9	6	6	6	5	4
7	12	11	11	11	8	7
8	10	7	7	7	7	6
Total	100	105	105	105	64	51

Source: Authors' elaboration based on data from Secretaría de Salud (DGIS) [36].

Table 3: Types of PHUs and the availability of their services.

Facility Type	Main service capacity (inhabitants)	Complementary Service Coverage				
		CS1	CS2	CS3	CS4	CS5
1	3,000	0	0	0	0	0
2	6,000	0	0	0	0	0
3	9,000	1	1	1	0	0
4	12,000	1	1	1	0	0
5	15,000	1	1	1	1	0
6	18,000	1	1	1	1	0
7	21,000	1	1	1	1	1
8	24,000	1	1	1	1	1
9	27,000	1	1	1	1	1
10	30,000	1	1	1	1	1
11	33,000	1	1	1	1	1
12	36,000	1	1	1	1	1
Critical coverage radius (km)		5	5	5	10	10

Source: Authors' elaboration based on data from Secretaría de Salud (DGIS) [36].

capacities as multiples of this value, in accordance with the 2010 guidelines set by the **Mexican Ministry of Health**. The availability of these services for each facility type is presented in the following five columns as binary values (1 denoting service provision, 0 denoting absence). The potential to upgrade existing facilities to a higher-tier category depends on the specific type of settlement, incorporating factors such as population density, infrastructural development, and the overall needs of the community. Furthermore, the critical coverage radius (Rs) in kilometers for each complementary service is presented as a key aspect of the proposed analysis.

Budget determination

For the empirical analysis, five different budget scenarios were generated, as shown in **Table 4**. B1 is the minimum budget to have feasible solutions and B5 is the maximum budget required to get the best

Table 4: Budget scenarios for each region (1×10^3 MXN).

Region	Budgets				
	B1	B2	B3	B4	B5
1	439	579	859	1,138	1,418
2	714	838	1,088	1,337	1,586
3	1,062	1,315	1,821	2,327	2,834
4	1,022	1,203	1,565	1,927	2,288
5	874	934	1,054	1,174	1,294
6	595	709	939	1,169	1,399
7	731	895	1,222	1,548	1,875
8	1,354	1,651	2,245	2,839	3,434

Table 5: Ranges of Z_2 used for the Epsilon constraint method for Region and Budget (1×10^3 MXN).

Region	Z_2	B1	B2	B3	B4	B5
1	Min	865	928	999	1,032	1,039
	Max	879	938	1,003	1,033	
2	Min	2,512	2,609	2,748	2,796	2,808
	Max	2,649	2,724	2,789	2,808	
3	Min	1,133	1,273	1,411	1,508	1,524
	Max	1,178	1,297	1,443	1,513	
4	Min	2,096	2,209	2,328	2,373	2,379
	Max	2,176	2,257	2,347	2,377	
5	Min	3,290	3,354	3,397	3,411	3,413
	Max	3,413	3,413	3,413	3,413	
6	Min	1,254	1,345	1,445	1,490	1,497
	Max	1,363	1,416	1,478	1,496	
7	Min	1,712	1,809	1,931	1,980	1,989
	Max	1,809	1,878	1,960	1,986	
8	Min	1,148	1,365	1,538	1,600	1,611
	Max	1,271	1,411	1,556	1,602	

possible values for both objectives (Z_1 and Z_2) given the other constraints. To obtain the value of the minimum budget (B1), the problem was solved with the objective of minimizing the total cost, while removing constraint (9), and keeping all the other constraints. The objective function value obtained corresponds to B1. For the maximum budget (B5), the problem was solved with both objective functions (1) and (2) separately, and then, the problem was solved again by minimizing the total cost with the objective functions (1) and (2) as constraints using the values of the objective function obtained as bounds. The objective value of this last problem was used as B5. Then, B2, B3, and B4 represent budgets equally distributed between B1 and B5.

Table 6: Data regarding the five budget scenarios in each region.

Region	Budget (1×10^3 MXN)	Pareto Set Points	Mín. Unit Distance (m)	Max. Unit Distance (m)	Mín. % of demand coverage	Max. % of demand covered	Average Computing Time (s)
1	439	9	1,353	1,376	79	80	17
	579	6	1,352	1,376	85	86	7
	859	3	1,352	1,375	91	91	29
	1139	2	1,352	1,361	94	94	14
	1418	1	1,352	1,352	95	95	1
2	714	69	1,279	1,427	88	93	442
	838	57	1,279	1,421	91	95	238
	1088	53	1,279	1,412	96	98	108
	1337	33	1,279	1,362	98	98	103
	1586	1	1,279	1,279	98	98	12
3	1062	32	1,726	1,783	62	64	195
	1315	35	1,726	1,781	70	71	228
	1821	16	1,726	1,769	77	79	378
	2328	13	1,726	1,750	83	83	100
	2834	1	1,726	1,726	83	83	19
4	1022	54	1,385	1,420	85	88	126
	1203	49	1,385	1,416	89	91	89
	1565	33	1,385	1,413	94	94	66
	1927	21	1,385	1,417	95	96	52
	2289	1	1,385	1,385	96	96	20
5	874	43	906	1,063	96	100	216
	934	48	906	987	98	100	172
	1054	28	906	927	99	100	38
	1174	12	906	908	100	100	15
	1294	1	906	906	100	100	80
6	595	68	1,505	2,311	77	83	1,087
	709	53	1,505	2,153	82	86	1,163
	939	41	1,505	2,058	88	90	618
	1,169	33	1,505	1,916	91	91	558
	1399	1	1,505	1,505	91	91	6
7	731	66	1,289	1,485	84	88	154
	895	60	1,289	1,485	88	92	159
	1222	52	1,289	1,444	94	96	102
	1549	25	1,289	1,345	97	97	38
	1875	1	1,289	1,289	97	97	70
8	1354	75	1,535	1,736	63	70	174
	1651	37	1,535	1,604	75	78	105
	2245	31	1,535	1,592	85	86	108
	2839	13	1,535	1,551	88	88	296
	3434	1	1,535	1,535	89	89	32

Epsilon constraint implementation

In the epsilon constraint method, one objective function is defined as a constraint of the problem. In this case, the objective function Z_2 was changed to constraint as is shown in Section 4. The bound of this constraint was gradually modified to generate different Pareto points. In this case, one hundred equidistant bounds of Z_2 were generated. The ranges of the bounds obtained with the lexicographic optimization for each region and budget are shown in Table 5. It can be observed that for budget B5, there is only one unique solution.

RESULTS AND ANALYSIS

To solve all integer programming models generated with the Epsilon-constraint method, the Branch-and-Bound algorithm from CPLEX 20.1 solver was used, with the callable library of C++. The experiments were conducted on a computer with an Intel(R) Core (TM) i5-4590 processor running at 3.30 GHz, supported by 16 GB of RAM, and operating under Windows 10. All instances were solved with a CPU time limit of one hour.

Table 6 presents statistics for the five budget scenarios in each region. It covers the number of Pareto set points, the minimum unit distance, the maximum unit distance, the maximum percentage of demand covered, the minimum percentage of demand covered, and the B&B CPU time to solve the instances. To calculate the minimum unitary distance, the total distance traveled was divided by the total demand. Additionally, covered demand represents the average of the covered demand from the five services analyzed. It is important to note that the distance pertains to the Main Service (MS), while coverage applies to the Complementary Services (CS).

A total of 100 iterations were attempted for each instance of the model to determine the Pareto set in each region using the AUGMECON2 method. It is crucial to note that each instance involves solving the problem in a specific region with a defined budget. There is a significant variation in the number of Pareto points found and the percentage of demand covered based on the budget invested. For instance, for region 1 with a minimum budget of 438 million Mexican pesos (MXN), nine points out of one hundred Pareto points were obtained, covering up to 80% of the demand in the best case. Conversely, with the highest budget close to 1418 million MXN, only one point was identified in the Pareto frontier, covering 95% of the demand, representing a noteworthy 15% increase. The number of Pareto points varied from region to region, due to the size of the region and the number of demand points. The average computation time can be observed in column 8 for each region, with the overall average computation time being 286 seconds. This is a reasonable computation time, as there is no need to employ a heuristic procedure to solve the problem.

Two regions were selected as examples to show the Pareto frontiers for the different budgets. These results are presented in Figures 3 and 4, revealing distinct behaviors for both frontiers. For instance, region 5 corresponds to the region where the City of León is located, an urban area with advanced

infrastructure that already satisfies most needs, as depicted in Figure 3. Even with a minimum budget (B1), over 95% of the demand can be covered on average with complementary services. In contrast, in the rural region of San Luis de la Paz, classified as region 8, there is a noticeable need for more substantial investment. This is particularly evident when utilizing the maximum budget (B5) to ensure coverage of complementary services, only 90% of the demand was covered on average, as illustrated in Figure 4. This *variability* highlights the essential link between needs and budgetary amounts, determined by specific factors. Demographic differences, prevalent health conditions, geographic accessibility, socio-economic levels, and existing infrastructure play pivotal roles in this context. Larger populations or those

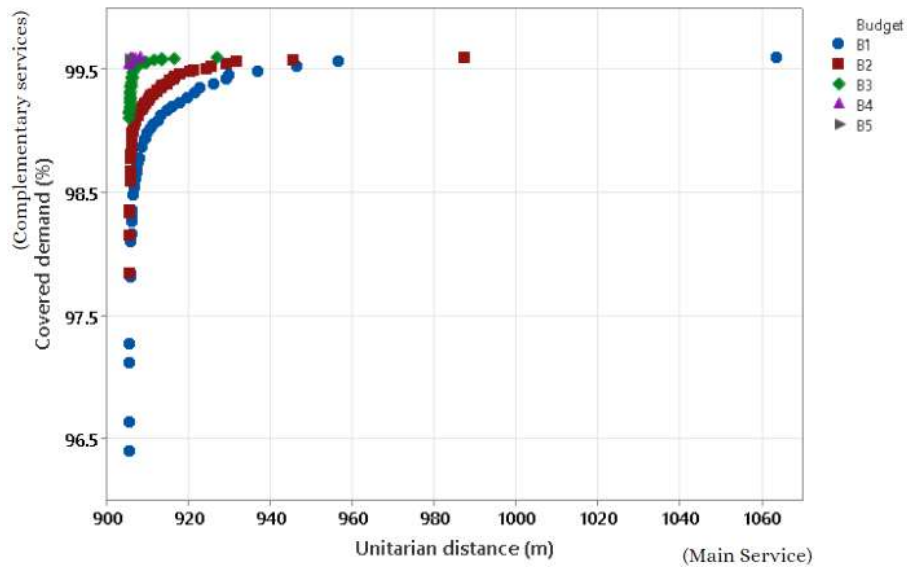


FIGURE 3: Representation of the Pareto Frontier of region 5.

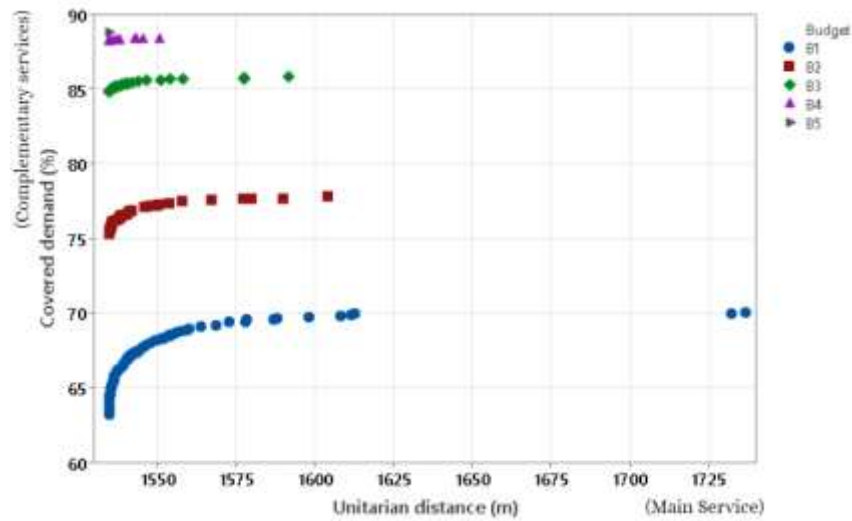


FIGURE 4: Representation of the Pareto Frontier of region 8.

with higher health challenges may require proportionally higher investment, while geography and socio-economic disparities also influence health demand and the need for investment. A meticulous assessment of these factors is essential to tailor health investment strategies that address the specific needs of each region.

Exemplification of results

In this section, the detailed results of a solution are presented. One solution of the Pareto set was chosen for each region for budget B2. To select a solution, the results were standardized with a scale from 0 to 1 for both objectives, where 0 represents the best solution for both objectives. Then, per region, the Pareto point with the Euclidean distance nearest to (0,0) was selected to exemplify the solution of the problem. In Figure 5, the Pareto set of each region for budget B2 is shown, highlighting with red the selected point.

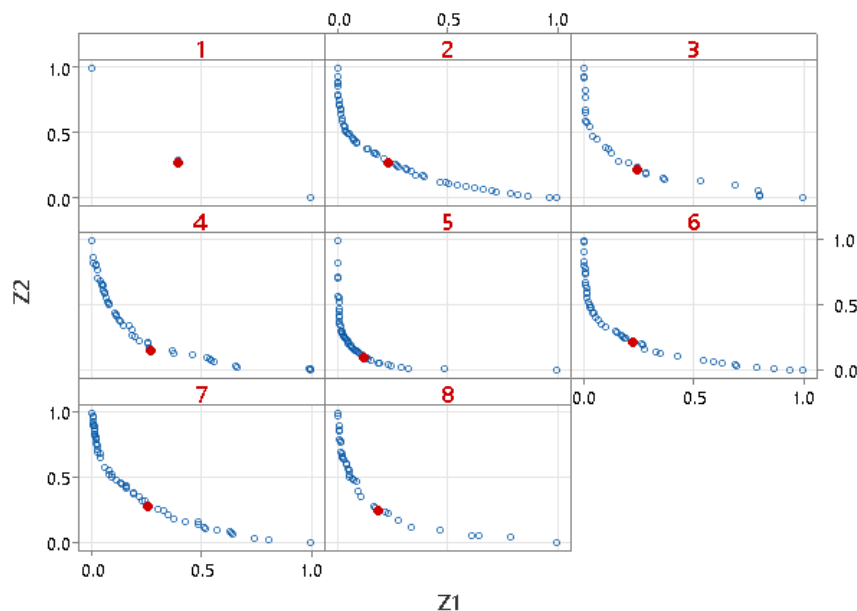


FIGURE 5: *The standardized Pareto set of each Region with a budget B2.*

Figure 6 illustrates the graphical representation of integrating the solutions of all the regions. The location of all facilities is shown, identifying the existing PHU that remains equal (HU), potential candidate sites with new PHUs (CS), and PHUs that have been upgraded (UPGRADE). There is a total of 853 existing PHUs, 486 candidate sites for new PHUs, and 170 PHUs that were upgraded with budget B2. The allocation of demand points for the main service is depicted in plot 7b, with connecting lines and colors representing demand allocation to each PHU, averaging a Euclidian distance of approximately 2.083 km for each assignment across all regions.

The coverage of complementary services is displayed in plots 6 c–e. Black points represent demand points and circular shapes represent healthcare units providing the complementary service. Any point covered by the circular shape indicates the coverage radius of PHUs with the complementary service installed. All relevant information about these healthcare units with complementary services is presented

in Table 7. For instance, 76% of demand points are covered for CS1, representing 91% of the total demand. It is observed that the same solution was found for CS2 and CS3 due to their identical coverage radius and availability in the same types of facilities. For CS4, there are 96 PHUs with this service, accounting for 9.63% of the total. For CS5, 71% of demand points are covered, representing 85% of the total demand. Overall, these solutions provide short assignment distances for the main service, and the coverage level of complementary services is highly efficient. CS5 has the lowest coverage rate; a strategy to improve its coverage could involve promoting collaboration between PHUs to share resources and optimizing CS5 coverage, especially in areas with higher demand but underutilized PHUs.

Table 7: Data related to facilities with complementary services.

Service	Complementary services				
	Nutritional counseling	Dental care	Psychological attention	Clinical analysis	Imaging
PHUs with service	241	241	241	96	85
% of PHUs	24.17%	24.17%	24.17%	9.63%	8.53%
% of demand coverage	91%	91%	91%	86%	85%
% demand point coverage	76%	76%	76%	73%	71%

CONCLUSIONS

In this article, the planning of primary healthcare infrastructure has been addressed with a specific focus on the Mexican healthcare system, considering the challenges of ensuring equitable access to essential services under limited-resource conditions. The results emphasize the critical importance of achieving comprehensive medical service coverage to improve care delivery in resource-constrained environments. A significant inverse relationship between travel distance and total investment costs has been identified, highlighting the need for efficient allocation of healthcare resources and strategic network design, particularly in settings with restricted budgets, which are common in developing countries.

The proposed bi-objective mixed-integer programming model has proven effective for simultaneously addressing facility location, capacity expansion, and complementary service integration. By leveraging real data from the state of Guanajuato, the study demonstrates the model's applicability and relevance, strengthening its role as a decision-support tool for healthcare network planning. Additionally, the

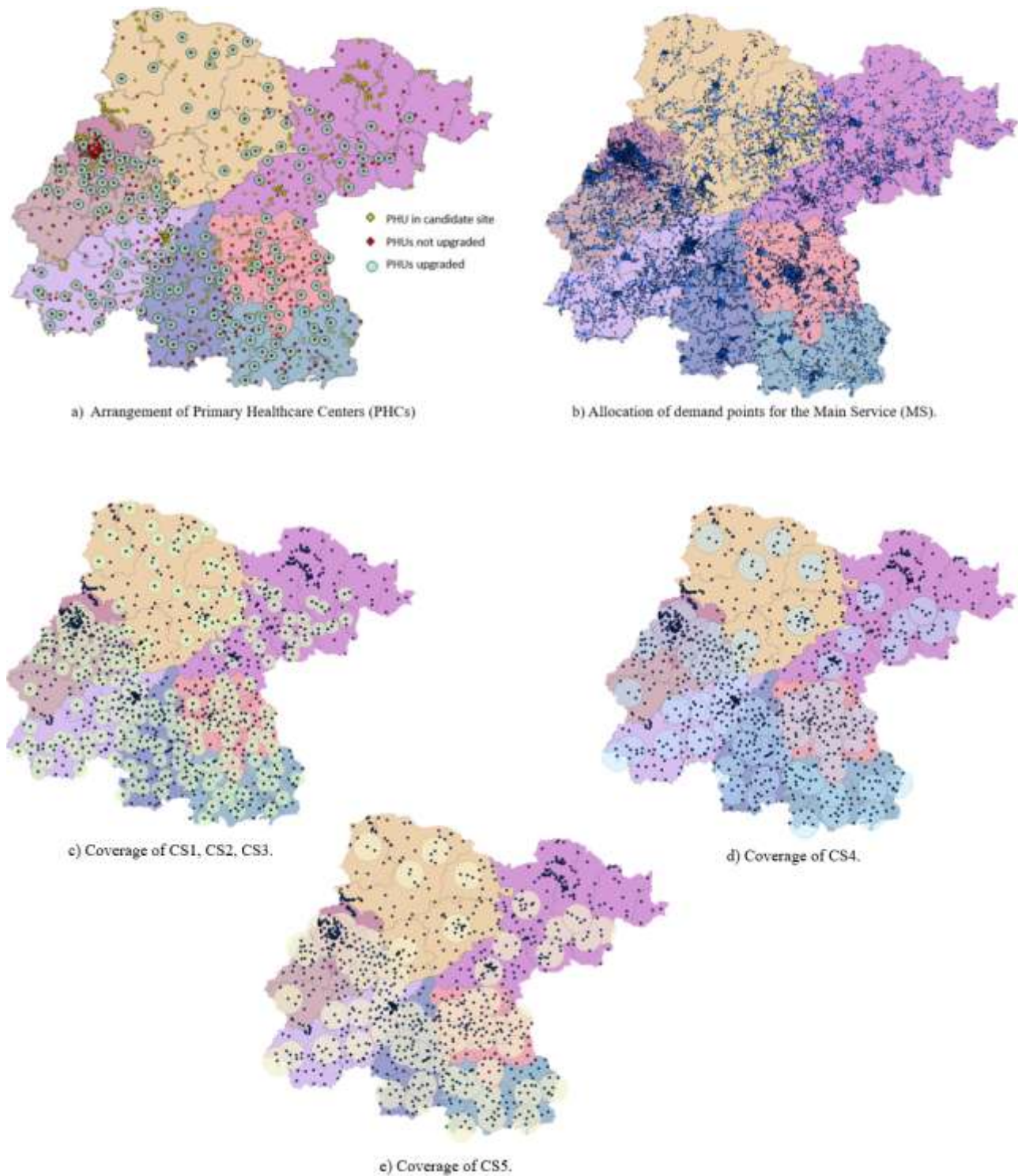


FIGURE 6: *Graphical Representation of the solutions in the state of Guanajuato.*

optimization of complementary service coverage under strict budgetary constraints has been shown to be critical for achieving balanced and equitable access to healthcare. Although the focus has been on the Mexican healthcare system, the methodology can be readily extended to other developing regions with similar structural and socio-economic limitations.

From a broader perspective, this work frames healthcare infrastructure planning within the context of a multi-tier service supply network, where decisions on facility siting, resource allocation, and service portfolio design closely mirror challenges traditionally addressed in supply chain network optimization. This cross-disciplinary perspective underscores the potential to leverage techniques from supply chain research to enhance resilience, equity, and efficiency in healthcare delivery systems.

Future research will explore advanced multi-objective optimization approaches to improve Pareto frontier generation, develop heuristics and decomposition techniques to address large-scale scenarios, and extend the case study to a nationwide analysis. Additionally, integrating infrastructure from other healthcare institutions such as the Mexican Social Security Institute (IMSS), the Institute for Social Security and Services for State Workers (ISSSTE), and the Social Security Institute for the Mexican Armed Forces (IMSSS) into the planning framework is identified as a relevant direction to achieve coordinated and efficient healthcare service networks. Another promising direction is to strengthen the empirical basis of the case studies by incorporating more detailed data sources, such as road-network-based distance matrices or estimated travel times, particularly for coverage-related services. This would allow the model to capture accessibility conditions more accurately, especially in rural areas where distances and times may diverge significantly due to transportation constraints.

DECLARACIÓN DE CONTRIBUCIÓN DE AUTORES Y COLABORADORES

Michael J. Park: Curación de datos, Análisis formal, Investigación, Software, Visualización, Redacción – borrador original. **Rodolfo Mendoza-Gómez:** Conceptualización, Metodología, Supervisión, Validación, Redacción – revisión y edición.

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