Faculty of Economics and Business

Optimizing Stroke Care Accessibility for At-Risk Populations

Merel Bonewit
(11888601)

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Supervisor: Prof. dr. ir. D. den Hertog
Second assessor: Ir. B. van Veggel

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Abstract

To reduce the high mortality and disability rates caused by strokes, the second-leading cause of death globally, immediate treatment is essential. Establishing new stroke centers in areas with a high stroke burden is therefore crucial for improving stroke patient outcomes. However, due to the variability in stroke incidence across geographies and demographics, determining optimal locations for these facilities to maximize their impact is complex. This thesis develops a scalable and adaptable model aimed at optimizing the locations of new stroke centers in relation to at-risk populations, with the goal of enhancing accessibility and reduce treatment initiation times for acute ischemic stroke patients, thereby improving total stroke patient outcomes. By applying the developed model to both a high-income (Croatia) and a low-income country (Vietnam) with contrasting profiles but high stroke burdens, the study investigates a wide range of challenges to ensure the model's robustness and adaptability across various national contexts worldwide, and demonstrates the proof of concept.

The results of these tests reveal that the developed stroke center location model significantly enhances total patient outcomes in various contexts, outperforming the classical healthcare facility location model. This enhancement is primarily due to the incorporation of different stroke treatment windows or travel time zones into the optimization model. Further refinement is achieved by integrating stroke risk factors into the model, although considering age as a stroke risk factor only benefits the model when there are significant differences in age distribution across sub-regions within a country. Furthermore, the comparison of runtimes between the stroke center location problem for the tested countries indicates that the model exhibits scalability. Specifically, the runtime increases from 8-10 seconds for ~90,000 decision variables (Croatia) to 30-32 seconds for ~120,000 decision variables (Vietnam). This suggests that while the model's runtime grows with the number of decision variables, the increase is roughly proportional, confirming the model is scalable and remains practical for larger and more complex datasets.

The stroke center location model empowers policymakers to effectively allocate resources for stroke care, aiming to enhance total patient outcomes. The resulting Pareto curves reveal that the opening of new stroke centers significantly improves patient outcomes. Even limited investments in new centers yield substantial improvements in total patient outcomes by opening just a few stroke centers if strategically located in high-impact areas as identified by the model. However, while the initial stroke centers significantly improve outcomes, the benefits diminish with each additional center. When the model indicates that the incremental benefits do not justify its costs, policymakers should consider reallocating resources to alternative strategies aimed at enhancing stroke patient outcomes. Overall, this model provides a valuable tool for policymakers to strategically enhance stroke care infrastructure, leading to more efficient resource allocation and better patient outcomes. By prioritizing strategic placement and considering diminishing returns, the model helps ensure that investments in stroke care have the highest possible impact.

Contents

1 Introduction

This section provides an introduction to the research presented in this thesis. First, the broader context and the significance of the topic are discussed in Section 1.1. Subsequently, in Section 1.2, the resulting central research question and objective of this thesis are stated. The high-over approach to achieve this objective is sketched in Section 1.3. Lastly, Section 1.4 contains a roadmap of the structure of this thesis, briefly summarizing the content of each subsequent section.

1.1 Research Background

Worldwide, 12.2 million people suffer a stroke each year. With 6.5 million annual deaths, accounting for 11.6% of all deaths globally, stroke is the second-leading cause of death around the world. Currently, 101 million people are permanently disabled as a result of a stroke, and this number has almost doubled over the last 30 years due to population aging [1]. Therefore, strokes remain one of the major global health challenges. According to Advani et al. [2], immediate diagnosis and treatment are crucial for improved patient outcomes. The concept of the 'stroke treatment window' or 'golden hour', indicating the crucial time from symptom onset to effective treatment initiation, highlights the importance of immediate medical intervention. Treatment within the golden hour has been associated with improved outcomes, as earlier treatment of stroke patients significantly reduces brain damage incurred. For each minute that treatment initiation is delayed, approximately 2 million nerve cells die [2]. Therefore, to ensure quick intervention, stroke centers should be easily accessible. This relation underscores the necessity to optimize geographic accessibility to stroke care centers.

To improve patient outcomes by enhancing stroke care accessibility, it is critical to establish new facilities. When considering the allocation of limited funds towards establishing new stroke facilities, a decision must be made regarding their optimal location such that stroke outcomes are maximized. However, determining these optimal locations is complex due to the variability in stroke incidence across geographies [3]. Several studies such as Leira et al. [4] and Vogel et al. [5] already demonstrated the effectiveness of facility location models, including maximal covering location models, to optimize stroke center locations. Nonetheless, these studies only account for geographical variations in stroke incidence based on population density, while the geographical variation in stroke incidence is also primarily attributed to demographic factors [1]. Therefore, this thesis aims to optimize the distribution of stroke care centers relative to at-risk population.

This optimization problem exhibits similarities to the maximal covering location model, where the locations of a number of facilities are identified in such a way that the covered population is maximized [6]. Using an extension of the maximal covering location model, by incorporating different stroke treatment windows to reflect more realistic situations and demographic risk factors to identify population at-risk, this study aims to develop a scalable and comprehensive model to optimize the locations of stroke centers relative to at-risk populations, such that it enhances stroke care accessibility and reduces treatment initiation times, with the goal to improve total patient outcomes. The final model should be scalable and adaptable to enhance stroke care accessibility globally.

1.2 Research Question and Objective

The resulting research question of this thesis is: How can a scalable and comprehensive model be developed to optimize the distribution of stroke care centers in relation to at-risk populations, with the goal of enhancing access and reducing treatment initiation times of acute ischemic stroke, ultimately improving stroke patient outcomes? By developing such a model, this thesis aims to create a scalable and adaptable solution for enhancing stroke care accessibility worldwide.

This model is developed in collaboration with Analytics for a Better World (ABW). The goal of Analytics for a Better World is to empower nonprofits to apply analytics towards the United Nations Sustainable Development Goals. One of these Sustainable Development Goals is to ensure healthy lives and promote well-being for all, including universal health coverage and access to essential healthcare services [7]. This thesis aims to contribute to this goal by developing a software prototype for the stroke center location problem that can be integrated into the Public Infrastructure Service Access (PISA) toolkit of Analytics of a Better World, so that it helps policymakers make data-driven decisions to enhance stroke care accessibility. The objective of this thesis therefore is to develop a prototype model, that eventually can be integrated into the PISA toolkit, to support non-governmental organizations (NGOs) such as the World Bank, the World Health Organization (WHO), the African Medical and Research Foundation (AMREF), and others in their efforts to make progress on these critical global health challenges.

1.3 Approach

To develop such a model, we need to identify the optimal locations of stroke care centers in relation to at-risk population. This optimization problem requires a quantitative measure for the objective of the model. In this thesis, we aim to maximize the expected total patient outcomes for stroke patients, where we incorporate demographic stroke risk factors to identify at-risk populations and different stroke treatment windows to reflect a more realistic situation. To achieve this, we first need to establish a precise definition of expected total patient outcomes. For this, we clarify the definition of a stroke used in this thesis and introduce a quantitative measure for stroke patient outcomes, namely the NIH Stroke Scale. Additionally, we explore the effect of treatment initiation times within defined treatment windows on patient outcomes. Afterwards, it is crucial to identify demographic stroke risk factors that significantly affect overall stroke burden. By integrating these factors, we obtain the expected total patient outcomes, which are maximized as the objective of this thesis.

To formulate this maximization problem, we first explore general location problems of existing studies to use as a foundation for our optimization problem. Building upon these models, we provide the description and mathematical formulation of the binary linear programming model developed for the stroke center location problem of this thesis.

Finally, to create a model that is scalable and adaptable to various countries, we test the model on real-life cases. Hereby, we narrow the scope of this thesis to one high-income country and one low-income, both experiencing high stroke burdens. The examined high-income country is Croatia, whereas Vietnam is tested as low-income country. By concentrating on these specific contexts with contrasting profiles, a broad range of challenges is investigated. This way a robust model is developed that can be applied effectively in diverse and broad settings worldwide, such that it eventually can be implemented in the Public Infrastructure Service Access (PISA) toolkit.

1.4 Outline

The structure of this thesis is as follows. First, Section 2 defines expected total patient outcomes of stroke patients, which is used as quantitative objective of the stroke center location problem in this thesis. This optimization model is specified in Section 3, where first general location problems are explained and used as a foundation for our stroke center location problem. In Section 4, the collection and preprocessing of all data required for the model are described, including all data necessary for testing the model on the high-income and low-income country investigated in this thesis. Afterwards, the model is tested on these two countries: Croatia, representing a high-income country (Section 5), and Vietnam, representing a low-income country (Section 6). This investigation ensures the model's robustness across diverse and broad setting. The results of these cases are followed in Section 7 by a comparative analysis between both countries. Finally, the conclusion, including implications for policymakers, is given in Section 8. Here, also limitations and suggestions for further research are highlighted.

2 Expected Total Patient Outcomes

In this thesis, we aim to maximize the expected total patient outcomes for ischemic stroke patients. To achieve this, we need to identify all determinants of stroke patient outcomes to establish a definition and quantitative measure of expected total patient outcomes. First, in Section 2.1, we define strokes and introduce a quantitative measure for stroke patient outcomes, the NIH Stroke Scale. By utilizing this stroke scale, we can objectively quantify the impact of a stroke and its treatment on patient outcomes. Next, we explore the impact of different stroke treatment windows on patient outcomes in Section 2.2. Furthermore, in Section 2.3, we identify demographic factors that affect the risk of a stroke. These factors are essential for estimating the probability of stroke occurrences within different population groups, such that we can better predict and evaluate the expected patient outcomes per geographical region. Finally, by integrating all stroke determinants of this chapter, we can assess the expected total patient outcomes, such that we can use it as quantitative objective in this thesis.

2.1 The NIH Stroke Scale as Measure for Patient Outcomes

To effectively address the expected total patient outcomes, we start with defining strokes. A stroke, also known as a brain attack, occurs when the blood supply to part of the brain is blocked or when a blood vessel in the brain bursts. In either scenario, parts of the brain sustain damage or perish, potentially resulting in long-term disability or even death [8]. For the purposes of this paper, we solely focus on ischemic strokes, which arises when blood clots or other particles obstruct the brain's blood vessels, since this type constitutes approximately 87% of all stroke cases [9].

Secondly, as this thesis aims to optimize expected total patient outcomes of stroke patients, it is essential to specify a quantitative measure for patient outcomes. Measures for stroke outcomes have been widely studied over the years [10]. One of the most used and recommended measures for stroke severity in scientific research is the National Institutes of Health (NIH) Stroke Scale, as endorsed by studies such as those of Schlegel et al. [10] and Kwah et al. [11]. The NIH Stroke Scale at hospital discharge objectively quantifies post-treatment impairment caused by a stroke. It assesses the severity of stroke symptoms and neurological deficits ranging from 0 to 42 based on 15 aspects as illustrated in Figure 25 of the Appendix, with higher scores indicating more severe neurological deficit [11]. Due to the fact that this measure is easy to learn, widely used, can be performed rapidly on admission or discharge, and has predictive validity for long-term stroke outcome, the NIH Stroke Scale is an attractive candidate predictor of stroke outcome [10]. Therefore, in this thesis we use the NIH Stroke Scale median at hospital discharge as measure for patient outcomes.

The scores for stroke patients used in this thesis are based on the findings of Advani et al. [2], shown in Table 1. Remarkably, this table shows that variations in NIH Stroke Scale scores are demonstrated across different treatment initiation times and age groups. These distinctions are further explained in the subsequent sections.

NIHSS	**$\leq$ 60 Min.**	**61 - 180 Min.**	**181 - 270 Min.**	**$>$ 270 Min.**[1]
$<$ 80 Years	0	4	7	42
$\geq$ 80 Years	0	5	7	42

Table 1: NIH Stroke Scale Median at Hospital Discharge

[1]NIH Stroke Scale scores are not provided for arrivals $>$ 270 minutes by Advani et al. [2]. We assume that these patients experience the most severe stroke outcomes, and therefore assign them the highest NIH Stroke Scale.

2.2 The Effect of Early Treatment on Patient Outcomes

The distinction in different initiation treatment times is based on the association of earlier treatment with better stroke patient outcomes. Several studies such as Wessell et al. [12] and Saver et al. [13] emphasize the critical importance of immediate treatment for patient outcomes in stroke care, since for each minute that passes without treatment, the brain loses approximately 2 million cells. The vital period between onset of stroke symptoms and the treatment initiation is known as the 'stroke treatment window'. The 'golden hour' refers to a stroke treatment window of at most one hour, highlighting the necessity of quick medical intervention in case of a stroke. The above mentioned studies have shown that treatment within this golden hour is related to better patient outcomes, as it significantly reduces the extent of brain damage caused by a stroke. The findings of Advani et al. [2], presented in Table 1, illustrate the NIHSS median scores at discharge for different stroke treatment windows and age groups. These results substantiate that shorter treatment initiation times result in significant better patient outcomes. Thus, when optimizing patient outcomes for this thesis, we need to incorporate these different stroke treatment windows into the assessment of patient outcomes. This can be achieved by implementing distinct NIH Stroke Scale scores for different stroke treatment windows relative to the patient's travel time from symptom onset to the closest stroke care center.

For the specific stroke treatment windows, we adopt the time ranges proposed by Advani et al. [2], as given in Table 1. Here, Advani et al. use four different stroke treatment windows to measure stroke patient outcomes: within 60 minutes (the golden hour), between 61 and 180 minutes, between 181 and 270 minutes, and over 270 minutes (no timely access). It is worth noting that Advani et al. [2] do not provide a NIH Stroke Scale for patients arriving later than 270 minutes. Nevertheless, the only approved treatment for acute ischemic stroke, intravenous (IV) thrombolytic therapy with tissue plasminogen activator (tPA), ideally has to be given within a maximum of 4.5 hours after stroke symptoms started [14]. Therefore, we assume that patients arriving later than 4.5 hours experience the most severe stroke outcomes and hence assign them the highest possible NIH Stroke Scale.

2.3 Stroke Risk Factors and Occurrence Probability

The other distinction made by Advani et al. [2] suggests demographic variability in stroke burden. To identify population at risk, we assess demographic stroke risk factors such that we can accurately account for this in the expected total patient outcomes. As the demographic variability must be measurable to accurately quantify it, we only look at non-modifiable stroke risk factors that are openly available for each region and that significantly affect the probability of a stroke.

According to Kes et al. [15], age and gender are the non-modifiable variables with the most significant impact on stroke risk. Firstly, the study of Roy-O'Reilly et al. [16] demonstrate that age is the strongest non-modifiable risk factor for ischemic stroke, leading to higher morbidity in older stroke patients. Specifically, the risk of stroke doubles for each decade after age 55 years [17]. Secondly, in terms of gender, age-adjusted comparisons show higher stroke risk for men than women [16]. However, these comparisons may oversimplify the complex relationship between sex and stroke risk at specific ages, given that sex-specific probabilities vary with age. Since the yearly probability of a stroke occurence does not significantly differ between men and women for the age groups used in this thesis [18], we opt to neglect gender as a factor in this study. Therefore, our study solely focuses on age as a stroke risk factor. For this, we adopt the age groups proposed by Advani et al. [2] in Table 1 to remain consistent. These age groups can be categorized as individuals younger than 80 years and individuals of 80 years and older.

To incorporate this demographic risk factor in expected total patient outcomes, we obtain the probability of a stroke occurrence across different age groups within the countries of interest. This probability, defined in this thesis as the yearly probability of a stroke occurrence for an individual of a specific age group, can be estimated by dividing the yearly number of ischemic stroke incidences per age group by the total number of inhabitants for that respective age group.

Finally, using this definition and the definitions from the previous sections, we can calculate the expected total patient outcomes for ischemic stroke patients. This involves integrating the NIH Stroke Scale across different age groups and treatment windows with the yearly probability of a stroke for each age group. By aggregating the expected patient outcomes across all age groups and treatment windows, we account for the impact of earlier treatment and demographic risk factors on the overall stroke burden and obtain a quantitative measure to optimize stroke care locations to improve patients outcomes.

3 Optimization Model

In this section, we introduce the stroke center location problem of this thesis. As this optimization problem builds on the foundation of the classical facility location problem, we start by exploring location problems based on existing literature in Section 3.1. Developing an extension of these model, in Section 3.1, we discuss the stroke center location problem of this thesis and explain how it can be transformed into a mathematical optimization model that can be solved using optimization solvers.

3.1 Literature Review of Location Problems

Here, we examine location problems as the foundation of this thesis. First, we explore the classical facility location problem, discussed in Section 3.1.1. However, while this facility location problem primarily aims to minimize costs associated with travel distance or time, a related variant of the facility location problem known as the maximal covering location problem maximizes the population coverage or accessibility, making it more relevant for the objective of this thesis. Hence, in Section 3.1.2, we look in detail at the maximal covering location problem.

3.1.1 Facility Location Problem

The facility location problem has been extensively studied by various researchers over the last century with many real-life applications in a wide range of public and private industries, including logistics, supply chain management, urban planning, public transportation, and telecommunications [19]. The application to healthcare facility locations has also been thoroughly investigated. Ahmadi et al. [20] provide an overview of all methodologies and models used in optimizing the locations of healthcare facilities from 2004 onwards. Although this survey paper highlights the extensive research conducted on healthcare facility location problems over the past two decades, none of the studies have integrated geographical variations resulting from demographic risk factors. This thesis aims to improve existing healthcare facility location models by bridging this gap in the literature.

The classical facility location problem considered in this thesis is uncapacitated, meaning that stroke patients are never denied care due to capacity constraints at the healthcare facilities. In this problem, the optimal locations for facilities to serve a set of demand nodes are identified while minimizing costs. Using the formulation of Postek et al. [21], the mathematical model of this problem can be given as follows:

$$\underset{(x,y)}{\text{Minimize}} \quad \sum_{j \in J} c_j x_j + \sum_{i \in I} \sum_{j \in J} h_{ij} y_{ij} \tag{1a}$$

$$\text{Subject to:} \quad \sum_{i \in I} y_{ij} \leq n x_j \qquad \text{for all } j \in J \tag{1b}$$

$$\sum_{j \in J} y_{ij} = 1 \qquad \text{for all } i \in I \tag{1c}$$

$$y_{ij} \in \{0, 1\} \qquad \text{for all } i \in I, \text{ for all } j \in J \tag{1d}$$

$$x_j \in \{0, 1\} \qquad \text{for all } j \in J \tag{1e}$$

where

Sets:

I = set of demand nodes (households or clusters of households);
J = set of potential facility locations;

Parameters:

c_j = costs of building facility j;
h_{ij} = costs incurred (travel distance) to satisfy the demands of household (cluster) i at facility j;

Decision variables:

$$x_j = \begin{cases} 1 & \text{if facility } j \text{ is built;} \\ 0 & \text{if not;} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \text{if household (cluster) } i \text{ is served at facility } j; \\ 0 & \text{if not.} \end{cases}$$

This model aims to minimize the total costs, consisting of set-up costs and costs related to the travel distance or time, as given in equation (1a). The minimization of the set-up costs in the objective function reflects the limited budget that policymakers have for opening stroke center facilities. Given that the policymaker will use the entire budget and that the set-up costs for each stroke center at existing hospital are equal as assumed in this thesis, the facility location problem now solely focuses on minimizing the total travel distance or travel time to a center for all households subject to several constraints. Constraint (1b) ensures that a facility can only serve households when it is actually built. Additionally, constraint (1c) guarantees that every household is served by at least one facility, regardless of their travel distance or time. Finally, constraint (1d) and constraint (1e) enforce binary decisions on both decision variables.

One of the major drawbacks of this facility location problem is its computational complexity. This complexity arises primarily from the double indexing of the decision variable y_{ij}. Consequently, finding an optimal solution is extremely challenging and time-consuming, especially given the scale of problems that we attempt to tackle in this thesis, involving multiple thousand household points and potential stroke center locations. When more facilities or more demand nodes are added to the model, the increased problem size also increases the number of parameters proportionally, leading to an even more complex model [22].

To address this challenge and reduce computational overhead, we look into a lighter computational model known as the maximal covering location problem, introduced in the next section. Unlike the facility location problem as discussed above, this problem contains decision variables with only single indexing, thereby significantly reducing the computational burden. Additionally, the maximal coverage location problem has a better fit to the problem of this thesis, since the allocation to the centers itself is not relevant for this thesis, only the travel distance or time to the nearest stroke center is of interest.

3.1.2 Maximal Covering Location Problem

The maximal covering location problem (MCLP) was first introduced by Church et al. [23] and since then widely studied by researchers as Zarandi et al. [6], ReVelle et al. [24] and Berman et al. [25]. This problem optimizes the location of a number of facilities on a network in such a way that the covered population is maximized. Here, a facility covers a household (custer) if it is established within a distance (or time) less than a certain threshold, or coverage radius, to the household (cluster). The mathematical model of this problem is as follows:

$$\text{Maximize} \quad \sum_{i \in I} a_i y_i \tag{2a}$$

$$\text{Subject to:} \quad y_i \leq \sum_{j \in N_i} x_j \qquad \text{for all } i \in I \tag{2b}$$

$$\sum_{j \in J} x_j \leq p \tag{2c}$$

$$y_i \in \{0, 1\} \qquad \text{for all } i \in I \tag{2d}$$

$$x_j \in \{0, 1\} \qquad \text{for all } j \in J \tag{2e}$$

where

Sets:

I	=	set of demand nodes (households or clusters of households);
J	=	set of potential facility locations;
N_i	=	$\{j \in J \mid d_{ij} \leq S\}$ = set of facility locations j that are within a distance S to household (cluster) i;

Parameters:

S	=	the maximal distance or travel time to a facility;
a_i	=	number of people in household (cluster) i;
d_{ij}	=	shortest travel distance or time from household (cluster) i to facility j;
p	=	number of facilities to be opened;

Decision variables:

$$y_i = \begin{cases} 1 & \text{if household (cluster) } i \text{ is covered by a facility within } S; \\ 0 & \text{if not;} \end{cases}$$

$$x_j = \begin{cases} 1 & \text{if facility node } j \text{ is opened;} \\ 0 & \text{if not.} \end{cases}$$

This model aims to maximize the population covered within the desired coverage radius S by at least one facility, as outlined in equation (2a). This can only happen when at least one facility is opened within the coverage radius of household i, imposed by constraint (2b). Furthermore, constraint (2c) imposes a budgetary constraint, limiting the number of new facilities to be opened to p due to limited available resources. Finally, constraint (2d) and constraint (2e) enforce binary decisions for both decision variables.

Due to the single index of the decision variables, this model is more appropriate for our thesis than the classical facility location model in Section 3.1.1. To illustrate this, suppose we optimize locations for 10,000 potential locations and 10,000 household clusters. This results in over 100,000,000 variables in total ($i \times j + j$) when using the classical facility location model, due to its double index variable y_{ij}. On the contrary, the maximal covering location problem avoids double indexing and hence optimizes only $i + j$ decision variables, resulting in a total of 20,000 variables. This makes the problem substantially more manageable and faster to solve. Thereby, the maximal covering location problem is more suitable for our thesis.

Nonetheless, note that the current objective of this maximal covering location model is to maximize population coverage rather than focusing directly on total patient outcomes, which is the primary goal of this thesis. Hence, it is necessary to refine this objective to incorporate stroke outcomes and probability of a stroke occurrence.

Furthermore, this model does not account for demographic variations across regions. Such variations play a significant role in understanding the distribution and impact of stroke care burdens in a country, according to Feigin et al. [1] and Kim et al. [3]. Hence, when identifying optimal locations that maximize total patient outcomes, as in this thesis, it is essential to incorporate these demographic factors to prioritize at-risk populations into the model.

Finally, the maximal covering location problem, as stated above, solely maximizes coverage strictly within the specified coverage radius, thereby excluding individuals residing just beyond the coverage threshold. To address this limitation, this thesis introduces different levels of coverage thresholds by adapting different travel time zones to opt for a more realistic and inclusive approach.

3.2 Stroke Center Location Problem

In this thesis we aim to find the optimal locations of new stroke care centers that maximize the total patient outcomes in a country, where we take the age as stroke risk factor, existing healthcare infrastructure, and different travel time to stroke care centers into account. We develop an extension of the maximal covering location problem for the stroke center location problem to avoid the need of a double index for households and facilities in the decision variable, thereby reducing the computational load significantly. The mathematical model of the resulting binary integer linear programming problem is as follows:

$$\underset{(x,y)}{\text{Maximize}} \quad \sum_{g\in G}\sum_{j\in J}\sum_{p\in P}(42 - s_{gj}) \cdot pr_g \cdot pop_{pg} \cdot y_{pj} \tag{3a}$$

$$\text{Subject to:} \quad x_i = 1 \qquad \text{for all } i = 1, ..., m \tag{3b}$$

$$\sum_{i=m+1}^{M} x_i \leq b \tag{3c}$$

$$y_{pj} \leq \sum_{i\in N_{pj}} x_i \qquad \text{for all } j \in J, \text{ for all } p \in P \tag{3d}$$

$$\sum_{j\in J} y_{pj} = 1 \qquad \text{for all } p \in P \tag{3e}$$

$$y_{pj} \in \{0, 1\} \qquad \text{for all } j \in J, \text{ for all } p \in P \tag{3f}$$

$$x_i \in \{0, 1\} \qquad \text{for all } i \in I \tag{3g}$$

where

Sets:

P	=	set of households or clusters of households: $p = 1, ..., H$;
I	=	set of hospital sites, where $i = 1, ..., m$ are already existing stroke centers at hospitals and $i = m + 1, ..., M$ are potential new stroke centers at existing hospitals;
J	=	set of travel time zones: $j = \{\leq 60 \text{ minutes}, 61 - 180 \text{ minutes}, 181 - 270 \text{ minutes}, > 270 \text{ minutes}\}$;
G	=	set of age groups: $g = \{< 80 \text{ years}, \geq 80 \text{ years}\}$;
N_{pj}	=	set of hospital sites i that are within travel zone j of household p;

Parameters:

s_{gj}	=	NIH Stroke Scale for age group g that can reach a stroke center within travel time zone j;
pr_g	=	yearly probability of a stroke for an individual of age group g;
pop_{pg}	=	number of people within household (cluster) p of age group g;
b	=	maximal number of new stroke centers to be opened (budget);

Decision variables:

$$y_{pj} = \begin{cases} 1 & \text{if household (cluster) } p \text{ is covered by a stroke center within travel time zone } j; \\ 0 & \text{if not;} \end{cases}$$

$$x_i = \begin{cases} 1 & \text{if a stroke center at hospital } i \text{ is opened;} \\ 0 & \text{if not.} \end{cases}$$

The objective of this model, expressed by equation (3a), is to maximize the expected total patient outcomes of the entire population of a country. If a stroke center is accessible within travel time zone j by household p ($y_{pj} = 1$), the potential benefit of treating stroke patients belonging to age group g within that zone is quantified as $42 - s_{jg}$. Here, s_{jg} denotes the severity of stroke consequences, as measured by the NIH Stroke Scale with a score of 42 representing the most severe stroke outcome. To evaluate the anticipated benefit, this value is multiplied by the annual probability pr_g of a stroke occurring to individuals within age group g. Finally, the expected total patient outcomes are obtained by multiplying this product by the number of individuals belonging to age group g within household p.

To account for the fact that there are already some existing stroke centers, constraint (3b) ensures that these facilities are set to open in the model. Constraint (3c) reflects the budget constraint, ensuring that at most b additional stroke care centers may be opened due to limited available resources. Constraint (3d) ensures that a household is connected to a stroke center within zone j only if there is a facility opened that is reachable within that certain travel time zone. The next constraint, (3e), guarantees that each household is served by a stroke center, exclusively by the nearest available stroke care center. Lastly, constraint (3f) and constraint (3g) enforce binary decisions for both variables x_i and y_{jp}.

In this model we make use of some assumptions for simplicity. Firstly, we assume that there are no capacity constraints at stroke centers, such that a stroke patient can never be denied care and that there is always sufficient availability of specialized medical staff. Additionally, we assume equal set-up costs for each stroke center at existing hospitals within the country, meaning the budget is constrained only by the number of stroke centers. Furthermore, we assume that patients recognize emergency immediately after symptom onset and do not delay seeking medical attention, although some patients may mistakenly believe that symptoms will resolve on their own and delay seeking hospital care. Lastly, for determining all possible locations for stroke care centers, we assume that stroke centers are only located within existing hospitals, as research highlights that integrating stroke care centers within hospitals is beneficial for several reasons. According to Rogers and Price [26], hospitals provide immediate access to emergency services and other specialized medical staff. This leads to less damage and improved patient outcomes. Secondly, Lip et al. [27] point out that integrating stroke centers into hospitals results in cost savings, since administrative and operational frameworks are already in place, reducing the need for substantial investment in new facilities. This makes it more feasible for governments and healthcare providers to expand stroke care service, especially in low-income countries. Therefore, we only take all existing hospitals of a country into account as possible locations for stroke centers in this thesis.

Lastly, note that this model solely uses the demographic factor age for identifying population at-risk, as explained in Section 2.3. However, when evaluating the optimal stroke centers locations for a country where there exists a significant difference in stroke probability between sexes, the model can be easily adjusted by incorporating sex as an additional index using a similar approach as for the age groups. This involves modifying the stroke probability parameter to reflect the yearly probability of a stroke for an individual in specific age and sex groups. Additionally, the household population parameter should be adjusted to account for the number of individuals of a certain age and sex within a (cluster of) household. These implementations result in a model that optimizes stroke care accessibility for at-risk populations considering both sex and age as stroke risk factors.

4 Data Collection and Preprocessing

In order to optimize locations for new stroke centers, we leverage the power of open-source data and tools. This section provides a detailed description of the collection and preprocessing steps required for our stroke center location model. This process starts in Section 4.1 with collecting data on income level, stroke burden and data availability to select countries for testing the optimization model on robust and diverse settings. Next, in Section 4.2 we extract administrative boundaries to ensure consistency with other geospatial datasets used for this model. We describe the data needed to calculate the probability of a stroke occurrence in Section 4.3. Subsequently, in Section 4.4, we explain how we collect demographic and geographic data on household and cluster them into larger groups to reduce computational load. Afterwards, we extract the locations of existing and potential stroke centers in Section 4.5. Finally, we obtain the geographical accessibility to stroke centers by using an isochronic analysis approach as described in Section 4.6.

4.1 Country Selection

Firstly, to create a model that is scalable and adaptable to various countries, we narrow the scope of testing the model to one high-income country and one low-income, both experiencing high stroke burdens. By concentrating on these specific contexts with contrasting profiles, a broad range of challenges is investigated. In this manner a robust model is developed that can be applied effectively in diverse and broad settings worldwide. The selection of these countries is based on a comparative analysis among countries with respect to the burden of strokes, income level and data availability in each country.

Firstly, to analyze the burden of strokes in a specific country, we examine national data on stroke-related mortality rates, incidence rates, and its ranking among national causes of death. This comprehensive approach helps in understanding the impact of strokes across different countries. We finally select two countries facing a high stroke burden in order to accurately assess the impact of the model.

The income level of a country is determined by its gross national income (GNI) per capita, which is openly accessible through the World Bank [28]. The World Bank uses this metric to classify each country into low-income (below 1,085 GNI per capita), lower-middle-income (1,085 - 4,225 GNI per capita), upper-middle-income (4,226 - 13,205 GNI per capita) or high-income (above 13,205 GNI per capita). For this thesis, we select one country with a high stroke burden from the low- or lower-middle-income category and one from the upper-middle- or high-income category to test the model's adaptability to various countries with contrasting profiles.

Lastly, the selected countries should have up to date and openly available data on all relevant aspects discussed in the subsequent sections of this chapter to ensure the feasibility and accuracy of the model.

Using these three criteria, Croatia is selected as a high-income country. This high-income country suffers from a significant stroke burden, with 178 annual stroke deaths per 100,000 inhabitants [18], placing it among the top five European countries in terms of stroke mortality [29]. Although the country established improved diagnostic and treatment options by opening in total 10 stroke centers over the past two decades, Croatia has not yet achieved the substantial decrease in stroke mortality and disabilities as seen in Western European countries [30]. This indicates potential for optimizing the locations of new stroke care centers to improve total patient outcomes.

As low-income country, Vietnam is selected. Vietnam faces a substantial burden of stroke, with stroke being the primary cause of death in the country [31]. It has on average 141 deaths per 100,000 inhabitants annually [18]. A recent study of Mai et al. [32] shows that with an annual incidence rate of 161 strokes per 100,000 inhabitants Vietnam needs 316 stroke units nationwide. However, only around 100 stroke care centers are currently established. Therefore, optimization of new established stroke centers in Vietnam is of significant importance.

After this selection, we need to collect and preprocess data on both selected countries required to test the model.

4.2 Administrative Country Boundaries

To begin with, we extract geospatial information on administrative boundaries for these countries by utilizing Global Administrative Areas (GADM) data. GADM provides maps and spatial data for all countries and their subdivisions. In this thesis we use the currently available version, namely version 4.0. We apply this on country level to retrieve high spatial resolutions of the administrative country boundaries. This step is crucial to ensure consistency with the geospatial data of households and stroke center in the subsequent sections.

4.3 Probability of a Stroke Occurrence

Secondly, to collect the probability of stroke occurrence across different age groups within the selected countries, we use Global Burden of Disease (GBD) data provided by the Institute For Health Metrics And Evaluation [18]. The GBD study is the largest and most comprehensive effort to quantify health loss across countries worldwide. Among other health information, this study provides the number of incidences of ischemic strokes, categorized by country, age, and gender. We leverage the latest GBD incidence figures from 2019 to compute the stroke occurrence probability. Since this dataset exclusively provides incidence data, we estimate the probability of a stroke occurrence by dividing the total incidences of ischemic strokes in age group g in 2019 by the total number of inhabitants of age group g in 2019. In this manner we calculate the yearly probability of a stroke occurrence for an individual of age group g. These obtained probabilities for Croatia and Vietnam are given in Table 2, confirming that the likelihood of a stroke above 80 years is significantly greater than for younger individuals.

	Croatia	**Vietnam**
$<$ **80 Years**	0.0014	0.0010
$\geq$ **80 Years**	0.0128	0.0118

Table 2: Yearly Probability of a Stroke Occurrence

4.4 Households

Next, we extract all households decomposed into the age groups. For this we use the open source database of WorldPop [33], containing Open Spatial Demographic Data and Research. The specific datasets of WorldPop needed for this thesis is the population count based on age and sex structures ('constrained individual countries 2020 UN adjusted'). These datasets are partitioned into 5-year age intervals and provide count estimates for individual countries for 2020 at 100 meter spatial resolution, where country totals are adjusted to match the corresponding official United Nation population estimates. Adding all age ranges belonging to the age group for a specific household, provide us the coordinates and the number of people of a certain age group in that household. An overview of the obtained total population numbers across the age groups in Croatia and Vietnam is shown in Table 3.

To decrease the computational load, we cluster the obtained households into household clusters. We achieve this by dividing the country into grids of 1 by 1 kilometers for countries with less than 500,000 household clusters as obtained by the 100 meter spatial resolution, and into grids of 2 by 2 kilometers for countries with more than 500,000 household clusters. Subsequently, households within the same grid based on their geographic coordinates are clustered, and the centroid of each grid is used to represent the geometry of these clusters. This approach significantly reduces the number of household,

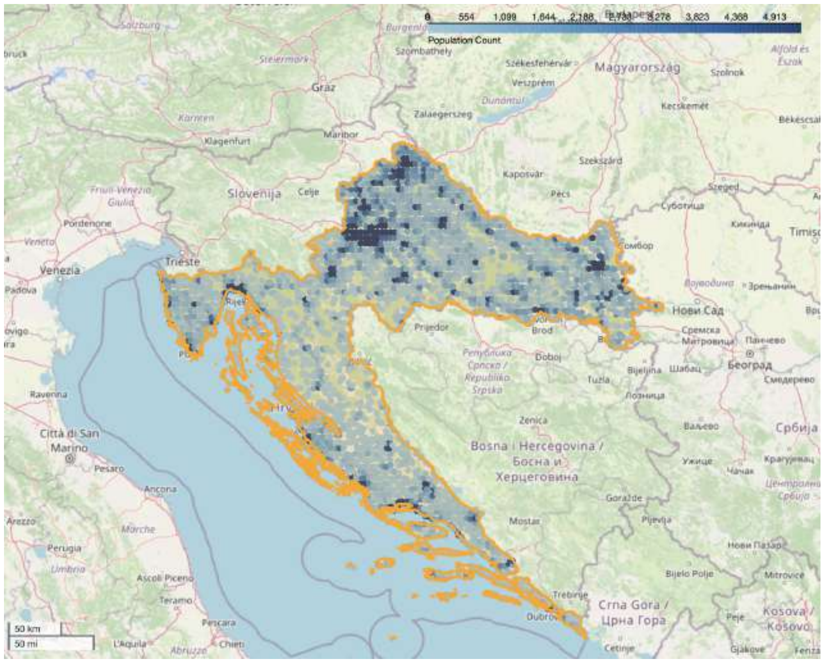

Figure 1: Population Density in Croatia on Household Cluster Level (5 x 5 Kilometers)

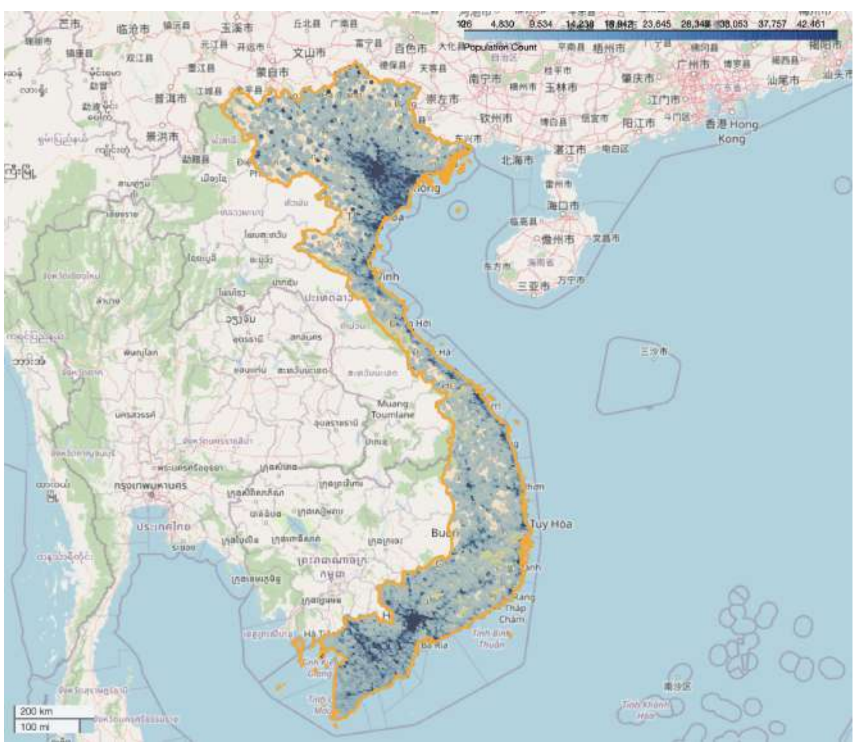

Figure 2: Population Density in Vietnam on Household Cluster Level (5 x 5 Kilometers)

	Croatia	Vietnam
Population $<$ 80 Years	3.85 million	95.47 million
Population $\geq$ 80 Years	0.23 million	1.93 million
Total Population	4.08 million	97.4 million

Table 3: Overview of Population Demographics

as illustrated in Table 4 for Croatia and Vietnam, thereby preventing the number of variables in our optimization model from exploding.

Finally, to ensure consistency by only including households within the administrative boundaries of the country, we intersect this data with the country boundaries obtained in Section 4.2 and create a GeoDataFrame of the results. The resulting households for Croatia and Vietnam are visualized (in clusters of 5 kilometers by 5 kilometers for illustration) in Figure 1 and Figure 2, with darker colours indicating higher population counts in the household cluster.

	Croatia	Vietnam
Households before Clustering	363,114	1,984,179
Final Household Clusters	22,373	30,130

Table 4: Number of Household Clusters before and after Clustering

4.5 Existing and Potential Stroke Care Centers

In determining all possible locations for stroke centers, we assume that stroke centers can only be located within existing hospitals, as explained in Section 3.2. To retrieve data on the locations of all healthcare facilities in the selected countries, the Overpass API of OpenStreetMap is utilized. This queries essential data such as names and coordinates of existing hospitals and clinics. However, we must be aware that this source is volunteer driven. Consequently, the list of healthcare facilities obtained by this query may not be exhaustive. In this thesis, this is not an issue as we aim to demonstrate the proof of concept, but when scaling and implementing this demo, this must be taken into account.

After obtaining a GeoDataFrame of all existing healthcare facilities by the Overpass API, we need to divide them into facilities with an already existing stroke care center and facilities with no yet existing but potential stroke care center. To acquire the existing stroke centers, we use locally curated lists. For Vietnam, we receive locally curated data from the World Bank. For Croatia, we curate the list manually based on the paper of Benkovic et al. [30]. Utilizing these location lists of existing stroke centers, we attempt to match these with the extracted existing healthcare facilities based on their geometry. Given that the coordinates of corresponding hospitals and centers obtained by different sources may slightly differ due to minor inaccuracies or variations in geographical coordinates, we use a buffer of 20 meters to match a stroke care center with a hospital. This buffer of 20 meters is based on a trade-off between avoiding false negatives and accounting for small discrepancies in coordinates of different datasets. However, since the Overpass API of OpenStreetMap may not provide an exhaustive list of all existing healthcare facilities in a country, we should assume that stroke care centers not matched with current hospitals are located in a hospital that still needs to be added to the existing hospital lists. The final dataframe consists of names and coordinates of all healthcare facilities and a dummy variable indicating whether the hospital already has a stroke care center or has no existing but potential stroke care center.

Again, to make sure we only obtain facilities within the administrative country boundaries for consistency, we intersect this data with the boundaries obtained in Section 4.2 and create a GeoDataFrame

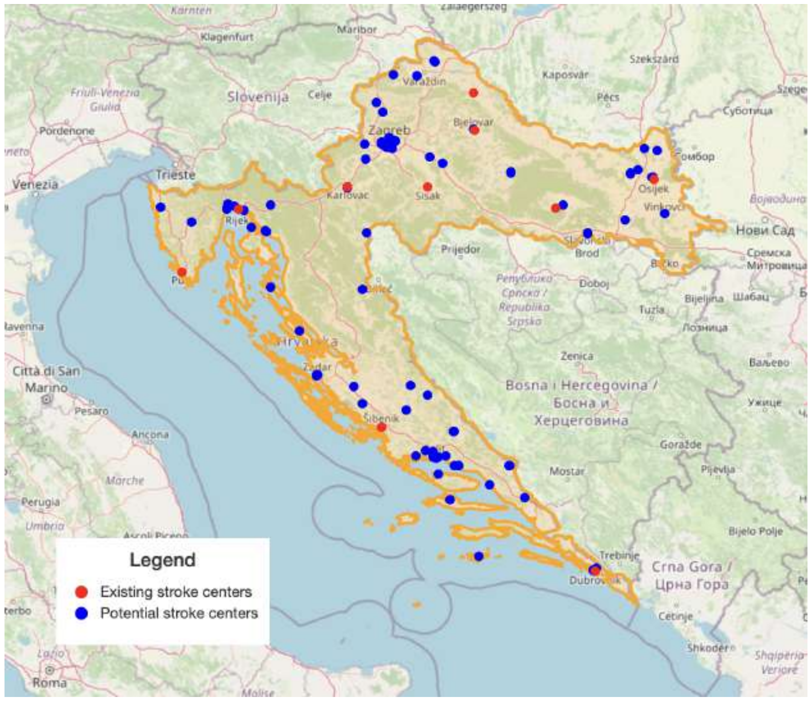

Figure 3: Established and Potential Stroke Care Centers in Croatia

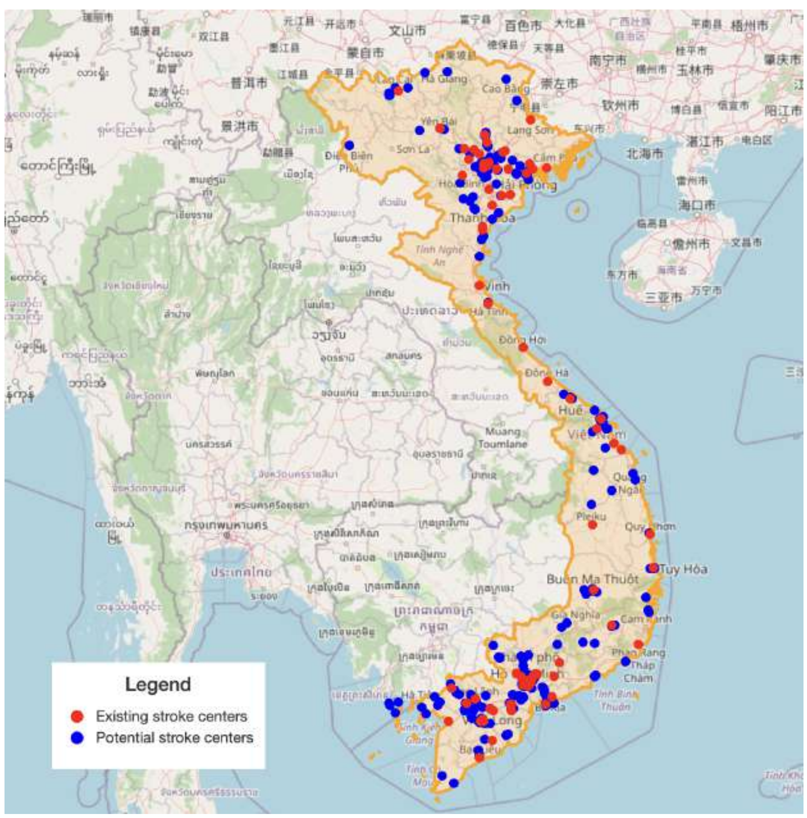

Figure 4: Established and Potential Stroke Care Centers in Vietnam

of the results. Following this approach for Croatia and Vietnam, we obtain the results shown in Table 5.

Currently, Croatia has 10 stroke care centers and 151 total healthcare facilities established. Therefore, there are still 141 potential locations for new stroke centers. The locations of established and potential stroke care centers in Croatia are depicted in Figure 3.

Similarly, Vietnam has 106 stroke care centers and 548 total healthcare facilities established. Therefore, there are still 442 potential locations for new stroke centers. The locations of all these centers are shown in Figure 4.

Remarkably, low-income country Vietnam has twice as many existing stroke centers per inhabitant as high-income country Croatia, even though Croatia faces a larger stroke burden, as highlighted in Section 4.1. Consequently, it is even more crucial to prioritize the establishment of new stroke centers in Croatia.

	Croatia	**Vietnam**
Existing Stroke Centers	10	106
Potential Stroke Centers	141	442
Total Healthcare Facilities	151	548

Table 5: Overview of Stroke Care Centers

4.6 Geographical Stroke Center Accessibility

Finally, we need to obtain the accessibility of household clusters to stroke care centers. The geographical accessibility of different household locations to current and potential stroke care centers is assessed by obtaining isochrones for all (potential) stroke care centers. An isochrone is a polygon representing the area reachable within a specific distance from a location. This is used in this thesis to identify the area of a (potential) stroke care center that can be reached within a specific time range by a specified mode of transport. Hereby, we assume the mode of transport will be driving, as we anticipate the use of ambulances in the event of a stroke.

To create isochrones, we utilize Mapbox API, a tool for spatial analysis. However, using this tool, our capabilities are bounded by the constraints imposed by the Mapbox API. One of these limitations is the maximum distance constraint, which restricts us to only generate isochrones within a maximum road distance of 100 km. Therefore, to work within this restriction, we approximate the isochrones for different travel time ranges based on an assumed average ambulance speed of 44 km/h, including set-up time and medical care provided at the patient's location, in line with the findings of Lupa et al. [34]. Considering both the journey to the patient's location and the return trip to the hospital, this average ambulance speed translates to an effective (round-trip) speed of roughly 22 km/h. This speed can be adjusted for different countries to reflect their respective transportation infrastructure and emergency response capabilities, which is crucial for the accuracy and adaptability of the model. However, using a round-trip speed threshold higher than 22 km/h may not be feasible due to the maximum distance constraint imposed by the Mapbox API. To mitigate this issue, one potential solution is to locally set up a similar tool, OpenRouteService. Nonetheless, this approach requires a large amount of RAM on a local machine to ensure efficient processing. For the purposes of this thesis, the approximation of 22 km/h for both countries serves as a pragmatic compromise. This allows us to estimate the areas that can be reached within specific time intervals by ambulance transportation, thereby demonstrating the proof of concept effectively.

For the specific time intervals as discretization of travel time, we use the four different treatment initiation windows as defined in Section 2.2: within 60 minutes, between 61 and 180 minutes, between

181 and 270 minutes, and more than 270 minutes. By obtaining isochronic polygons for each existing and potential stroke care center using distance thresholds of 22 kilometers for 60 minutes, 44 kilometers for 180 minutes, and 99 kilometers for 270 minutes, based on the average ambulance speed, we can determine all clusters of households that have access to each (potential) stroke care center within the specific initiation time zone. The resulting polygons for the current stroke centers in Croatia and Vietnam are plotted in Figures 5 and 6 for illustration.

After obtaining the ID's of all household clusters that have access within a certain travel time zone for each hospital, we apply reverse mapping to obtain the accessible hospitals for each household cluster. The resulting sets of (potential) stroke center sites that are within a specific travel zone of a household cluster are added to the household GeoDataFrame of Section 4.4.

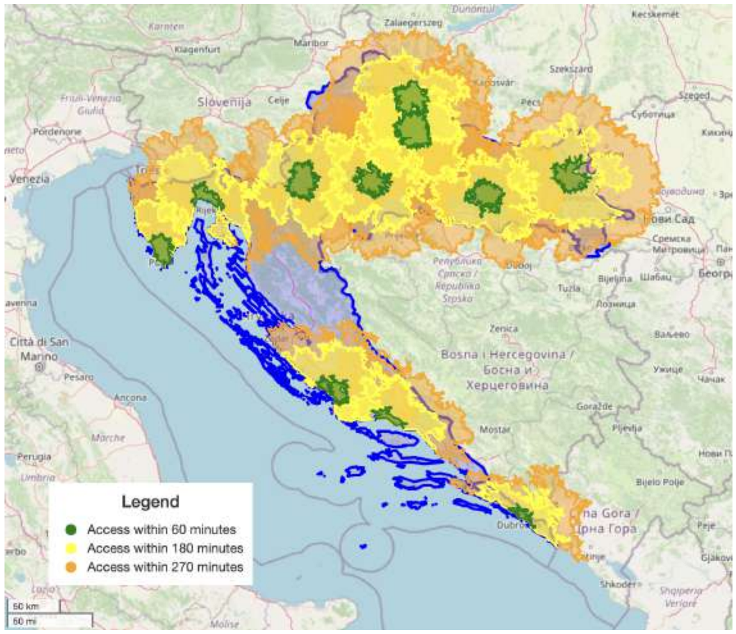

Figure 5: Obtained Polygons for Current Stroke Centers in Croatia

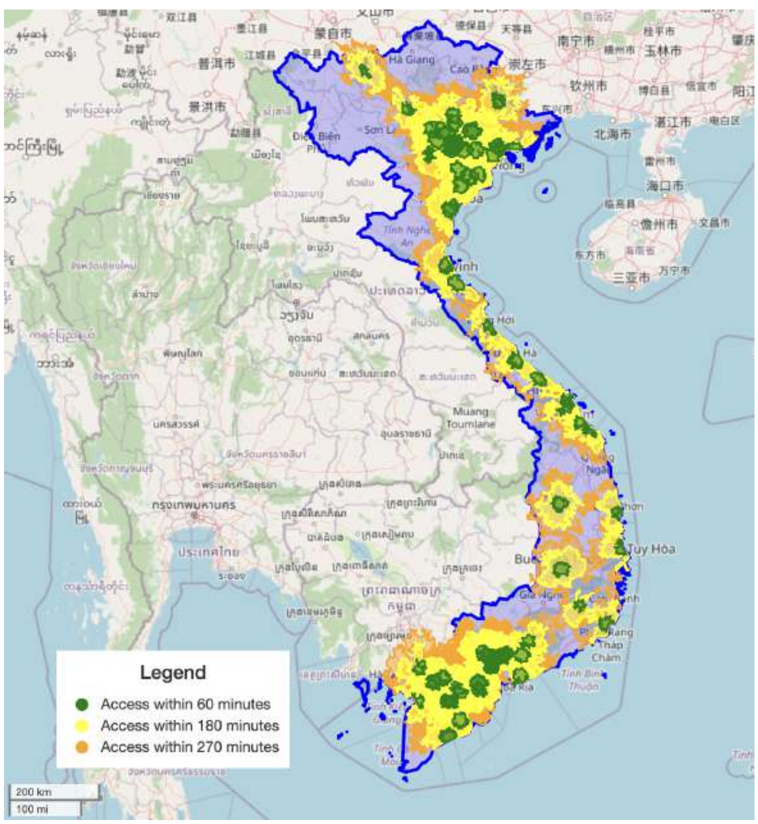

Figure 6: Obtained Polygons for Current Stroke Centers in Vietnam

5 Testing the Model on a High-Income Country: Croatia

By testing the model on one high-income country and one low-income country, each with contrasting economic profiles but both experiencing a high stroke burden, a broad range of challenges faced by the model is investigated. This way, the robustness of the model is tested, such that it eventually can be applied in diverse and broad settings worldwide. Based on these experiments, we start with describing the current situation concerning strokes in Croatia in Section 5.1. Afterwards, in Section 5.2, we analyze the results and implications for policymakers of solving the stroke center location problem in Croatia for various budget scenarios and different average ambulance speeds. Subsequently, Section 5.3 assesses the effectiveness of the current stroke centers in Croatia. Lastly, we compare the results of this thesis model with the classical healthcare facility location model in Croatia to quantify the added value of the model developed in this thesis in Section 5.4.

5.1 Current Situation in Croatia

Before optimizing the location of new stroke centers in Croatia, we define a baseline in this section by assessing the current situation in Croatia. Currently, only 20.3% of Croatia's population lives within the golden hour of a stroke care center, assuming an effective average ambulance speed of 22 km/h, as depicted in Table 6. Additionally, this table shows that 73.0% of the population can access a stroke center within 180 minutes, and 94.7% within 270 minutes. Consequently, 6.4% of all inhabitants lack access to a stroke center within 4.5 hours.

	Population	**Percentage of Population**
Within 60 Minutes	827,573	20.3%
Within 180 Minutes	2,978,393	73.0%
Within 270 Minutes	3,821,663	93.7%
Over 270 Minutes	258,910	6.4%

Table 6: Current Accessibility to Stroke Centers in Croatia

Figure 7 shows a heatmap of the population with access to the stroke centers currently established. The corresponding total patient outcomes are 293,051, used as baseline in the next section.

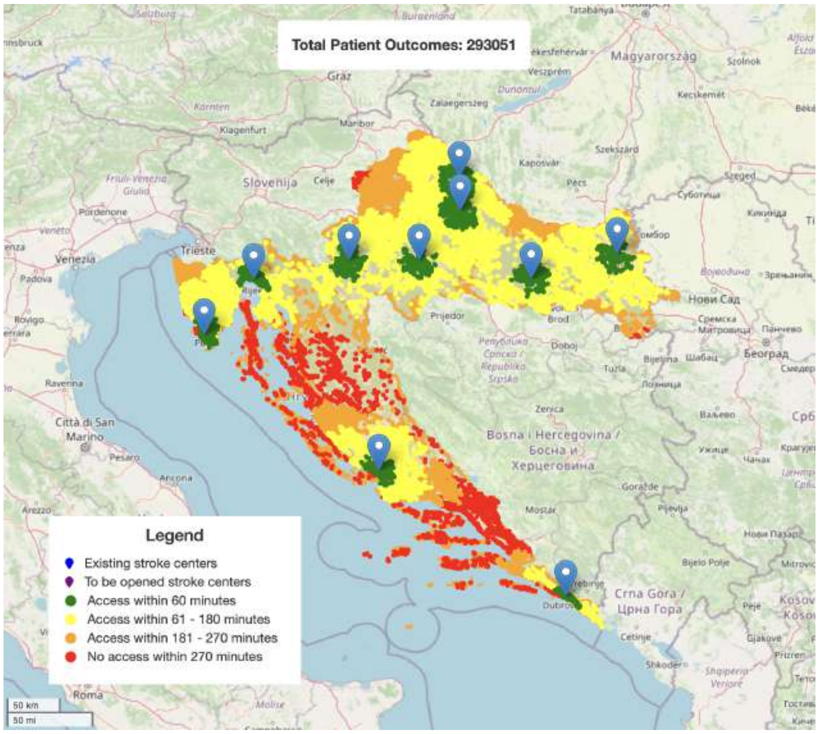

Figure 7: Heatmap of Accessibility with Current Stroke Centers in Croatia

5.2 Results of Stroke Center Location Model in Croatia

In this section, we first explore the model's scalability based on the runtimes of solving the problem for Croatia. Afterwards, the results of solving the stroke center location problem for Croatia are discussed and compared to the current situation in Section 5.1. Initially, we present Pareto curves illustrating the total patient outcomes and population access to evaluate the impact of opening new stroke centers. Afterwards, we deep-dive into these results by analyzing the results of several fixed budget scenarios. Lastly, a sensitivity analysis is conducted to assess the impact of average ambulance speed on total patient outcomes and population access.

5.2.1 Runtime and Scalability

Assessing the runtime of solving the optimization problem is essential to examine the model's scalibility, one of the key objectives of this thesis. Therefore, we calculate the runtime of solving the stroke center location model on the tested country of this section to assess its performance. These tests are conducted using Google Colab Pro, a cloud-based Jupyter notebook environment provided by Google. The notebooks are configured to use a Python 3 runtime environment, running on an AMD EPYC 7B12 processor with 8 CPUs (each processor having 4 cores), operating at 2.25 GHz, and equipped with 51 GB of RAM. Moreover, the optimization model uses a Gurobi solver with an academic license.

The stroke center location problem for Croatia optimizes approximately 90,000 decision variables. This includes 151 stroke center locations (x_i) and 22,373 household clusters each considered across four travel time zones (y_{ij}). The Gurobi solver solves this problem within 8 to 10 seconds, irrespective of the budget. This relatively short runtime demonstrates that the model is computationally efficient and suitable for pracitical applications.

5.2.2 Pareto Curves

To analyze the results of solving the stroke center location problem, we re-run the model for varying budgets and create Pareto curves of the results. Figure 8 illustrates such a Pareto curve for total patient outcomes against the maximal number of stroke centers that may be opened. This curve indicates a principle of diminishing returns, where the initial investment in opening stroke centers yields the highest benefits in terms of patient outcomes. Opening the first three stroke centers results in the most significant improvement in total patient outcomes. This suggests that these centers are strategically located in areas with the highest stroke burden or stroke patient density. Beyond the first three centers, the additional gain in patient outcomes per new center decreases. This diminishing return is typical in Pareto analysis, where the most critical interventions yield the highest returns. The maximal total patient outcomes possible with the potential location list equals 335,454. This maximum is achieved when 89 stroke centers are operational, including opening 79 new stroke centers. Beyond this point, adding more stroke centers does not further increase patient outcomes, indicating that the system has reached its optimal capacity. This can be explained by the fact that some inhabitants may never be able to reach any of the (potential) stroke centers quickly by ambulance, given they live in remote or isolated areas such as islands or mountains.

Similarly, the Pareto curve in Figure 9 shows the effect of the number of stroke centers on the population's access to treatment within the golden hour (60 minutes). The trend roughly mirrors that of patient outcomes, supporting the principle of diminishing returns. The first three stroke centers significantly increase the population's access to stroke care within the golden hour, indicating that these centers are located in high stroke burden areas that are currently underserved. After these initial centers are opened, each new center adds progressively less to the population coverage, reflecting the diminishing returns. After opening 79 new stroke centers, leading to 89 stroke centers in total, the maximal coverage within the golden hour of 78.4% is reached. Beyond this threshold, opening additional centers do not contribute to increase the percentage of population served within the critical time frame of the golden hour, since some inhabitants are not able to reach any of the (potential) stroke centers within an hour, given they live in remote or isolated areas.

Lastly, Figure 10 illustrates the Pareto curves for population coverage across different travel time zones to stroke centers in Croatia. Interestingly, if the budget increases, not only do total patient outcomes increase, but also does the coverage for 60 minutes, 180 minutes, and 270 minutes. Additionally, each coverage curve shows more or less diminishing returns. However, while the population with access within the golden hour converges after the establishment of 79 new stroke centers, the population with access within 180 minutes converges significantly faster. Therefore, fewer new stroke centers are needed to ensure that a substantial fraction of the population can access a stroke center within 180 minutes, compared to the golden hour scenario. Moreover, the population coverage for those within 270 minutes, as well as those who have no access within 270 minutes, stabilizes after the addition of just 14 new stroke centers, as shown in Table 21 in the Appendix. This suggests that after opening 14 new stroke centers, minimal additional benefit can be achieved by opening more stroke centers in terms of reducing the number of people who lack access within 270 minutes. These Pareto curves reveal that while extending coverage within shorter travel times requires a larger number of stroke centers, ensuring access within longer travel times (180 and 270 minutes) can be achieved more quickly and with fewer centers. Furthermore, it can be observed that the population without access can not be reduced to zero with the current (potential) stroke center set, since inhabitants living in isolated areas lack timely access to any potentially opened stroke center.

In summary, this analysis implies that while opening new stroke centers initially leads to substantial improvements in total patient outcomes in Croatia, these benefits diminish as additional centers are added. Therefore, the opening of the first few stroke centers yields the highest increase in total patient outcomes, provided they are located in areas that will have the most impact, particularly in underserved areas facing a high stroke burden. This emphasizes the need of strategically locating new stroke centers to maximize their impact on total patient benefits. However, after a certain threshold,

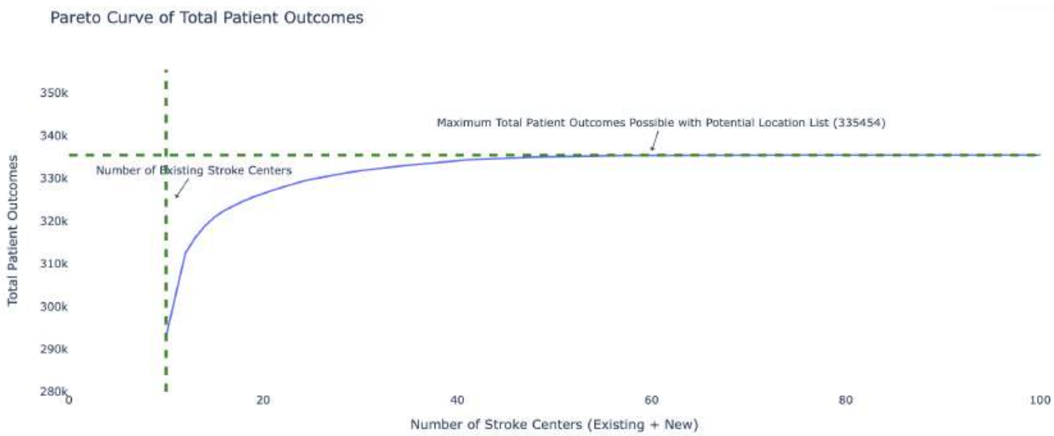

Figure 8: Pareto Curve of Total Patient Outcomes in Croatia

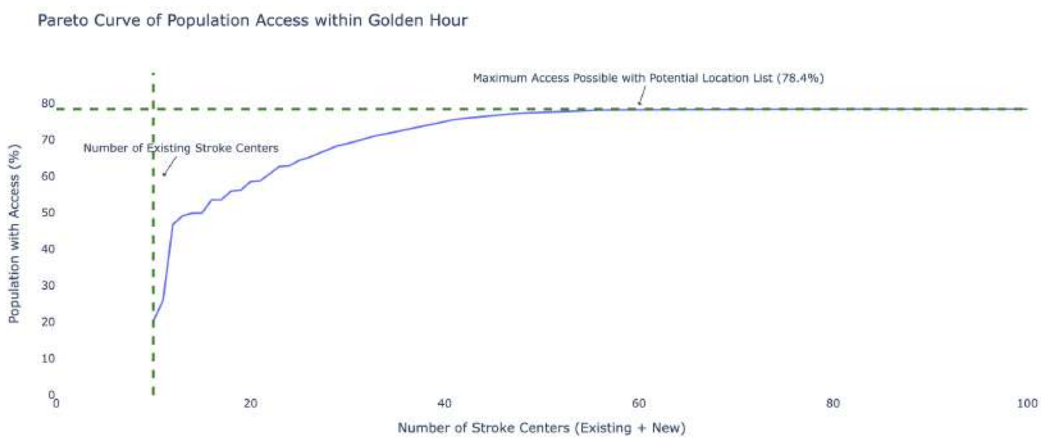

Figure 9: Pareto Curve of Population Access within Golden Hour (60 Minutes) in Croatia

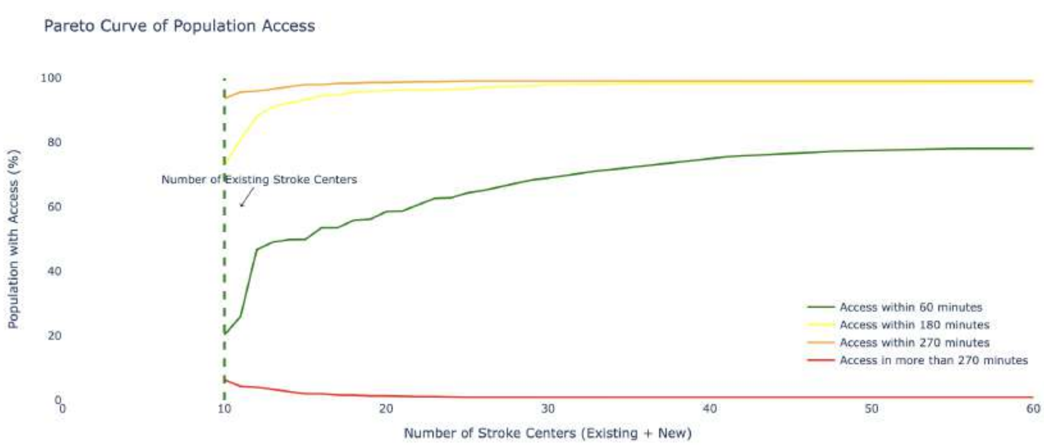

Figure 10: Pareto Curve of Population Access for each Travel Time Zone in Croatia

the investment in additional centers may not be justified by the incremental improvement in outcomes, and resources might be better allocated to other aspects of stroke care to achieve further improvements, such as improving the quality of existing stroke centers or setting up campaigns for stroke prevention. Utilizing this model will empower policymakers by making strategic decisions on the allocation of resources for stroke care and strategically locating new stroke centers.

5.2.3 Results for Various Fixed Budgets

To further evaluate the effectiveness of various fixed budgets in improving stroke care, we examine the outcomes associated with opening different numbers of new stroke centers. For this, we compare the current situation with scenarios involving the opening of one and five additional stroke centers.

The resulting optimal stroke center locations under these scenarios are detailed in Table 7. This table identifies the specific hospital locations considered most effective for opening new stroke centers based on maximizing the total patient outcomes. Remarkably, the optimal hospital for opening a single stroke center is not included in the list of optimal hospitals when five stroke centers are opened. This discrepancy arises because, as more hospitals are added, the areas they cover can overlap, leading to a different optimal set of locations that maximize total patient outcomes. Figure 12 and Figure 13 at the end of this chapter substantiate this, showing heatmaps of stroke center accessibility at the household cluster level and the locations of the existing and optimal new stroke centers for both budgets.

	Hospital Names (b = 1)	**Hospital Names (b = 5)**
1	Ljekarna Pablo	Dom zdravlja Kaštela
2		Dom zdravlja
3		Poliklinika Ribnjak
4		Dom zdravlja Korenica
5		Poliklinika Petrović

Table 7: New Stroke Centers at Hospitals in Croatia to be Opened (b = 5)

The impact on total patient outcomes and accessibility from opening these new stroke centers is quantified in Table 8. This table provides insight into the effect on total patient outcomes and access to timely stroke care by opening the new stroke centers.

	b = 0	**b = 1**	**b = 5**
Within 60 Minutes	20.3%	26.0%	49.9%
Within 180 Minutes	73.0%	80.9%	93.3%
Within 270 Minutes	93.7%	95.6%	98.0%
Over 270 Minutes	6.4%	4.4%	2.0%
Total Patient Outcomes	293,051	302,810	320,917

Table 8: Percentage of Population with Access to Stroke Centers in Croatia for Different Budgets

Currently, 20.3% of the population has access to stroke care within the golden hour (60 minutes), which is relatively low. A larger portion of the population, namely 73.0%, has access to stroke care within 3 hours, and 93.7% has access within 4.5 hours. However, there remains a population fraction of 6.4% without timely access within 270 minutes.

Introducing one additional stroke center increases the total patient outcomes by more than 3% and the population with golden hour access by almost 6 percent point, raising it from the current level to 26%. Additionally, the coverage within 3 hours increases to 80.9%, and within 4.5 hours to 95.6%. These improvements imply that the new center is strategically positioned to serve a high-stroke burden or previously underserved area. Furthermore, the population without access within 4.5 hours decreases by 2 percent point to 4.4%. This reduction indicates enhanced regional coverage and faster access to emergency care for a broader population segment by opening already one additional stroke center.

The introduction of five new centers boosts the total patient outcomes by 10% compared to the current situation. Additionally, the golden hour access is raised to almost 50% of the population. Similarly, the population with access within 3 hours increases to 93.3%, and within 4.5 hours to 98.0%. These increases suggest that the additional centers effectively fill critical gaps in the current stroke care infrastructure. Moreover, the percentage of the population without access within 4.5 hours drops to 2%. This near-universal coverage highlights the strategic benefit of opening multiple centers to ensure rapid access to stroke care, thereby improving total patient outcomes.

5.2.4 Sensitivity Analysis of Average Ambulance Speed

Next to the travel distance, there is another factor that has be taken into account when assessing the accessibility, namely the average ambulance speed. To evaluate the effect of the ambulance speed on the total patient outcomes, we also optimize the stroke center locations for a decreased average ambulance speed of 15 km/h and compare this to the previous results using a speed of 22 km/h.

Table 9 shows the optimal stroke centers resulting from solving the stroke center location problem with an average ambulance speed of 15 km/h. Remarkably, the optimal stroke center locations deviate from the optimal locations when assuming an average ambulance speed of 22 km/h, as showed in Table 7. This trend holds true for both budget scenarios and can be explained by the fact that lower average ambulance speeds increase travel times to stroke centers, resulting in reduced coverage areas. Consequently, the optimal locations that maximize total patient outcomes can differ based on varying population densities and demographics in these areas.

	Hospital Names (b = 1)	**Hospital Names (b = 5)**
1	Poliklinika Ribnjak	Poliklinika Ribnjak
2		Poliklinika Mešter
3		Ljekarna Božica Lončarić
4		Klinika za kožne i spolne bolesti
5		Poliklinika Petrović

Table 9: New Stroke Centers at Hospitals in Croatia to be Opened (b = 5, speed = 15 km/h)

As a result of the different optimal locations, the areas covered within different travel time zones, shown in Figure 14 and Figure 15 at the end of this chapter, also deviate from the higher speed scenario. Therefore, it is of great importance that the average ambulance speed is accurately measured when optimizing the locations of new stroke care centers to maximize their impact.

From Table 10, it is evident that, as expected, the coverage decreases with a decrease in average speed, while keeping the budget constant. However, opening additional stroke centers in case of an ambulance speed of 15 km/h leads to a more pronounced percent point increase in coverage for each time zone compared to the scenario with a speed of 22 km/h. Similarly, the increase in total patient outcomes associated with opening stroke centers is more substantial at 15 km/h compared to 22 km/h. Conversely, both coverage within the different travel time zones and total patient outcomes are higher for a higher average ambulance speed. Only in case of opening just one stroke center, population access within the golden hour becomes higher with a lower average speed. Nonetheless, this is compensated by the higher coverage for the other time zones, resulting in higher total patient outcomes in the 22 km/h scenario.

Average Speed	**15 km/h**			**22 km/h**		
Budget	**b = 0**	**b = 1**	**b = 5**	**b = 0**	**b = 1**	**b = 5**
Within 60 Minutes	17.0%	35.0%	44.6%	20.3%	26.0%	49.9%
Within 180 Minutes	38.1%	62.5%	82.0%	73.0%	80.9%	93.3%
Within 270 Minutes	73.8%	80.8%	94.0%	93.7%	95.6%	98.0%
Over 270 Minutes	26.2%	19.2%	6.0 %	6.4%	4.4%	2.0%
Total Patient Outcomes	226,529	258,049	305,045	293,051	302,810	320,917

Table 10: Population Coverage of Stroke Centers with Varying Average Ambulance Speed

In conclusion, the average ambulance speed should be accurately measured before policymakers use the model for optimizing the locations of new stroke care centers to maximize their impact, since the optimal locations depend on the average ambulance speed. Secondly, lower average ambulance speeds magnify the beneficial impact of opening additional stroke centers. However, a higher ambulance speed leads to significantly higher total patient outcomes and stroke care coverage for each travel time zone, when keeping the budget constant. This underscores the importance of a high ambulance speed as a critical factor influencing both the efficiency of stroke care delivery and overall patient outcomes. Therefore, policymakers should strive for higher average ambulance speeds by lobbying for better infrastructure, investing in the quality of the ambulances, or train ambulance drivers to improve their driving skills.

5.3 Effectiveness Analysis of Current Stroke Centers in Croatia

In this section we analyze the effectiveness of the current stroke centers in Croatia by considering a greenfield approach. We start with the greenfield situation in which no stroke centers are opened at all. Then, we maximize the locations of new stroke centers using the stroke center location model, where the budget equals the number of currently existing stroke centers, and we again assume an average ambulance speed of 22 km/h. By comparing the model's results of the greenfield situation to the current stroke centers, we can evaluate the effectiveness of the current stroke centers.

Figure 11 depicts the optimal stroke centers of the greenfield situation and the current stroke centers. Only four out of the ten currently opened stroke centers are optimal in the solution of the greenfield approach, and two optimal stroke centers are in close proximity to existing stroke centers. However, four existing stroke centers are not optimally positioned, as the optimal locations of these centers in the Greenfield situation largely deviate from the current centers.

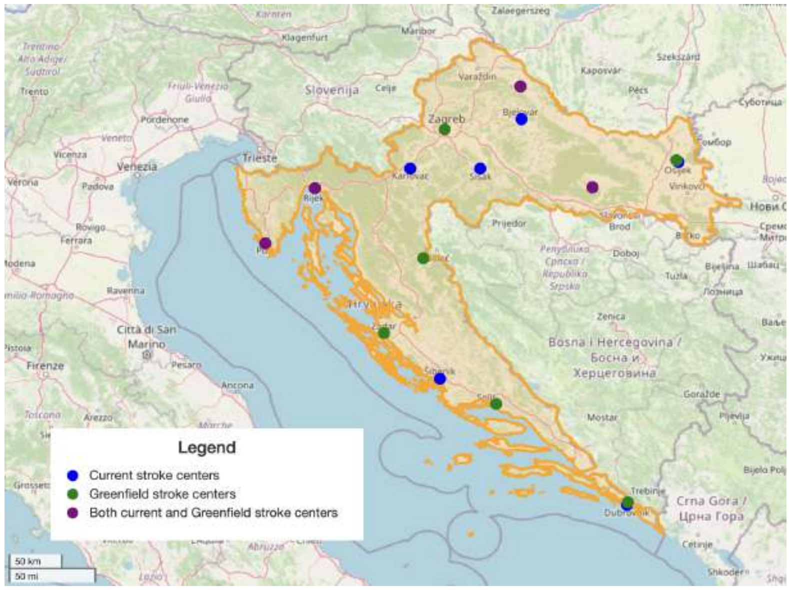

Figure 11: Current Centers and Optimal Centers in Greenfield Situation in Croatia

The finding that four existing stroke centers are not optimally positioned is substantiated by Table 11. This table illustrates that the population with access could be substantially higher when the current stroke centers were initially optimal located using the stroke center location model. Consequently, the overall patient outcomes could be enhanced by 7% compared to the current locations, highlighting the critical need to strategically locate new stroke centers using the model proposed in this thesis. Additionally, policymakers in Croatia could consider closing existing centers and reopening them at the found optimal locations based on these results, if the increased benefits outweigh the associated additional costs of closing and opening these centers.

	Current	**Greenfield**
Within 60 Minutes	20.3%	42.7%
Within 180 Minutes	73.0%	86.1%
Within 270 Minutes	93.7%	97.2%
Over 270 Minutes	6.4%	2.8%
Total Patient Outcomes	293,051	314,389

Table 11: Coverage and Patient Outcomes of Current Situation versus Solution of Greenfield Situation

5.4 Comparison of Results with the Classical Healthcare Facility Location Model in Croatia

In this section, we evaluate the added value of the stroke center location model developed in this thesis. We first assess the added value of this model for Croatia compared to the classical healthcare facility location approach, where only the golden hour coverage is maximized and no stroke risk factors are taken into account. Afterwards, we separately examine the contribution of incorporating different travel time zones and demographic risk factors for strokes, such as age, into our optimization problem. For all models, we assume an average ambulance speed of 22 km/h.

To assess the added value of the stroke center location problem developed in this thesis, we compare this model with the classical healthcare facility location model currently used in PISA. In this classical model, we optimize stroke center locations to maximize solely the golden hour coverage, and we neglect stroke risk factors. We can rewrite our model to the classical healthcare facility location model by setting the probability of a stroke constant for each age group, using a weighted average, and assigning weight only to the golden hour travel time zone in the objective function, using a NIH Stroke Scale of 42 for all other travel time zones to set their weights to zero. Note that the total patient outcomes must be computed manually thereafter, where we utilize the correct NIH Stroke Scale scores and stroke probabilities for accurately determining and comparing patient outcomes.

The results of the classical model and the model of this thesis are shown in Table 12. As expected, the population access within 60 minutes (golden hour) increases significantly more for both budgets using the classical approach, where the objective is to maximize golden hour coverage, compared to the approach presented in this thesis. However, the population coverage within 180 minutes and within 270 minutes is lower when using the classical approach. Consequently, more inhabitants lack timely access within 180 or within 270 minutes to a stroke center. Therefore, the total patient outcomes are lower when using the classical approach. In case of opening one additional stroke center, the total patient outcomes become 0.6% higher using the model of this thesis instead of the classical model. Additionally, in case of opening five stroke centers, the total patient outcomes of this thesis model increase by 4.1%. In summary, we can conclude that the stroke center location model of this thesis outperforms the classical healthcare facility location in terms of total patient outcomes in Croatia and thereby improves stroke care even further.

Facility Location Model	**Thesis**			**Classical**		
Budget	**b = 0**	**b = 1**	**b = 5**	**b = 0**	**b = 1**	**b = 5**
Within 60 Minutes	20.3%	26.0%	49.9%	20.3%	41.0%	55.7%
Within 180 Minutes	73.0%	80.9%	93.3%	73.0%	80.1%	91.6%
Within 270 Minutes	93.7%	95.6%	98.0%	93.7%	93.9%	96.4%
Over 270 Minutes	6.4%	4.4%	2.0%	6.4%	6.1%	3.6%
Total Patient Outcomes	293,051	302,810	320,917	293,051	300,941	308,348

Table 12: Comparison of the Stroke Center Location Model with the Classical Approach

To investigate this improvement in more detail, we separately examine the contribution of incorporating different travel time zones and demographic risk factors for strokes, such as age, into the optimization model solved for Croatia. We evaluate the added value of optimizing different travel time zones by comparing the model of this thesis to a model with zero weights in the objective function for all travel time zones except the golden hour zone, using a NIHSS score of 42 for these zones. For assessing the added value of incorporating demographic stroke risk factors to account for population at-risk, we compare the model in this thesis with a model where the probability on a stroke and the NIH Stroke Scale are held constant for both age groups, using weighted averages.

Interestingly, the findings suggest that the solution for Croatia, regardless of the budget, improves solely by optimizing different travel time zones, rather than focusing exclusively on the golden hour zone. Taking age into account as a stroke risk factor, however, does not contribute to improved patient outcomes in Croatia, as the model's solution remains unaffected by age incorporation. An explanation for this can be that the data for Croatia suggest that the age distribution does not show significant differences across sub-regions in Croatia. This observation aligns with findings that the percentage of people older than 80 years remains approximately constant (between 5.3% and 6.1%) across all household clusters throughout the entire country. Therefore, for Croatia, the improvement of the model of this thesis compared to the classical healthcare facility location model is solely due to incorporating different travel time zones.

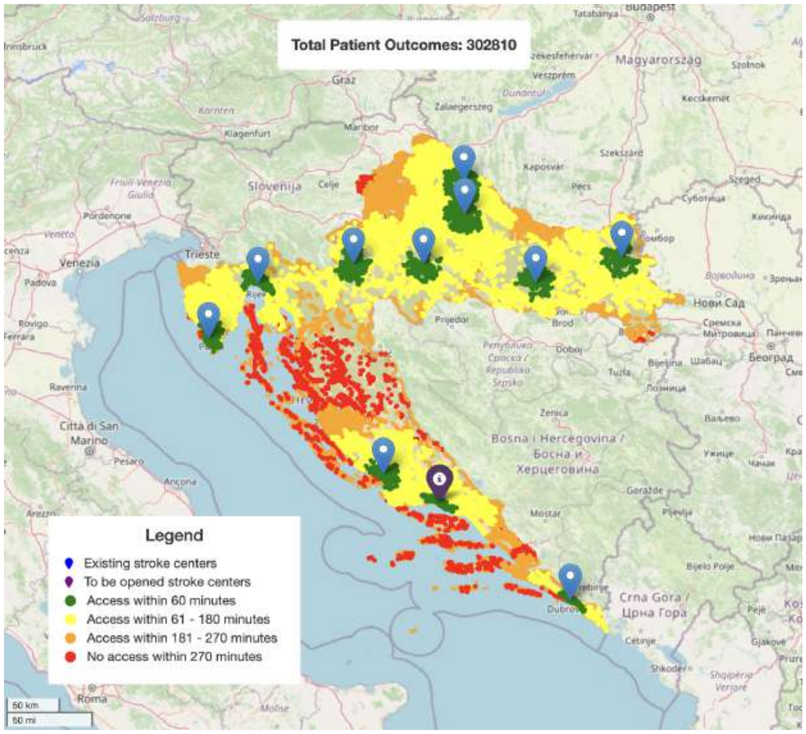

Figure 12: Heatmap of Accessibility with 1 New Stroke Centers in Croatia (b = 1, speed = 22 km/h)

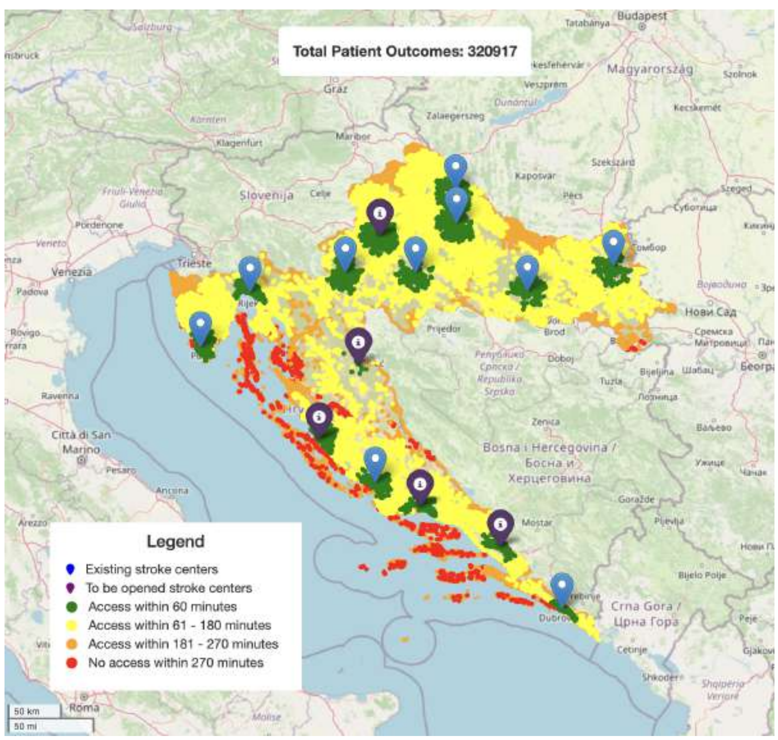

Figure 13: Heatmap of Accessibility with 5 New Stroke Centers in Croatia (b = 5, speed = 22 km/h)

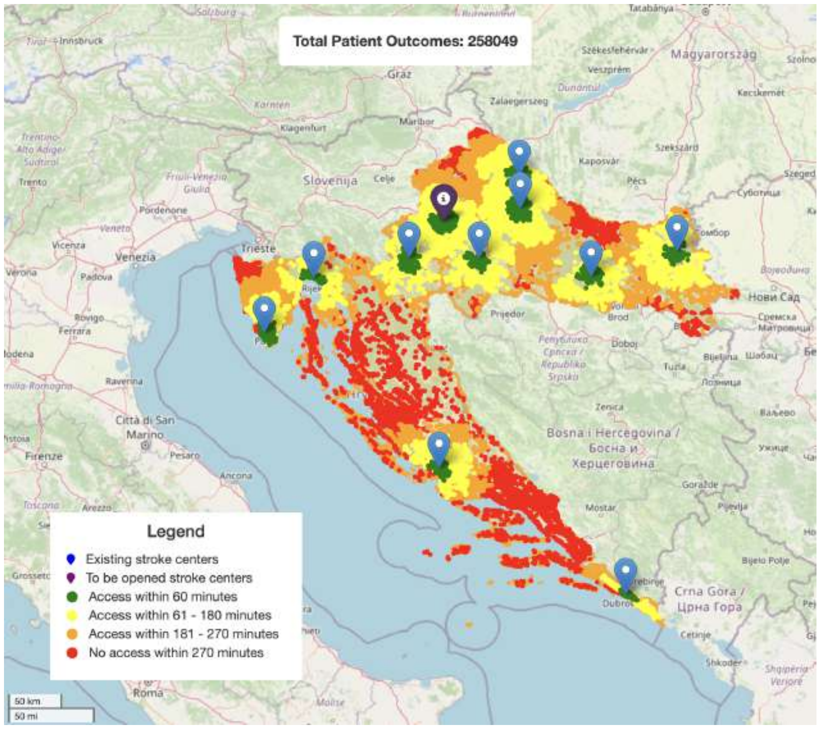

Figure 14: Heatmap of Accessibility with 1 New Stroke Centers in Croatia (b = 1, speed = 15 km/h)

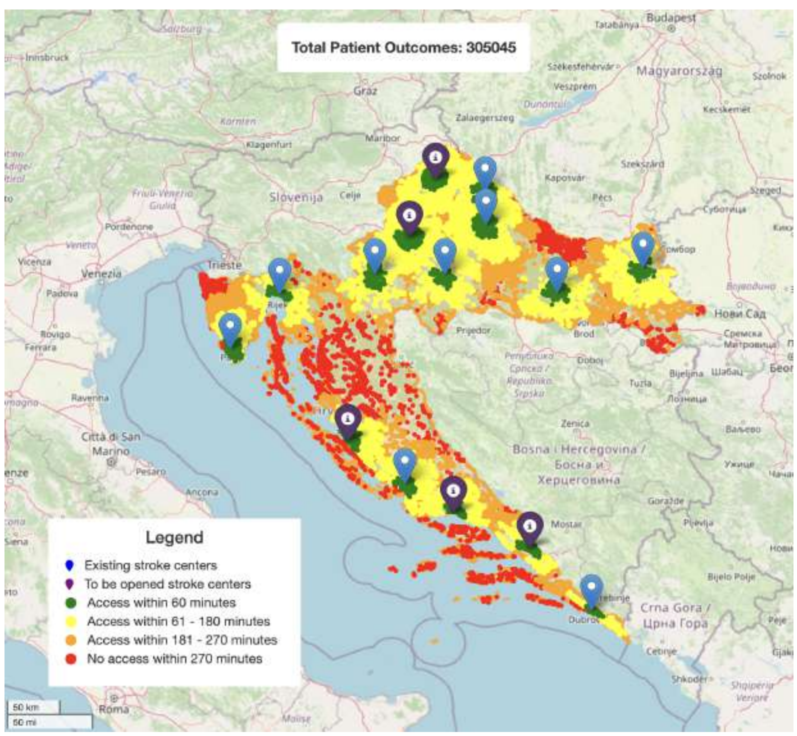

Figure 15: Heatmap of Accessibility with 5 New Stroke Centers in Croatia (b = 5, speed = 15 km/h)

6 Testing the Model on a Low-Income Country: Vietnam

Besides testing the model on a high-income country, the model is also tested on a low-income country to investigate a broad range of challenges faced by the model. This approach aims to assess the robustness of the model for application in diverse settings worldwide. Therefore, in this section, we conduct numerical tests of the stroke center location problem on a real-life case, focusing on the low-income country Vietnam. We begin with describing the current situation regarding strokes in Vietnam (Section 6.1). Subsequently, in Section 6.2, we examine the outcomes associated with solving the stroke center location problem in Vietnam for various budget scenarios and different average ambulance speeds. Then, Section 6.3 evaluates the effectiveness of the current stroke centers in Croatia. Lastly, we compare the results of this thesis model with the classical healthcare facility location model to quantify the added value of the model for Vietnam in Section 6.4.

6.1 Current Situation in Vietnam

First, we assess the current situation in Vietnam as baseline for the results of solving the problem in the subsequent sections. Vietnam currently has established 106 stroke centers spread over the country. The stroke center accessibility to these centers is given in Table 13. With these current established stroke centers in Vietnam, 49.5% of Vietnam's inhabitants can be served within the golden hour, assuming an average ambulance speed of 22 km/h. Within 180 minutes, 81.6% of the population can be treated in case of a stroke. Lastly, 73.3% of all inhabitants can reach a stroke center within 270 minutes. Consequently, over 9.5% of all residents lack access to a stroke center within 270 minutes.

	Population	**Percentage of Population**
Within 60 Minutes	48,193,408	49.5%
Within 180 Minutes	79,505,920	81.6%
Within 270 Minutes	88,145,664	90.5%
Over 270 Minutes	9,251,664	9.5%

Table 13: Current Accessibility to Stroke Centers in Vietnam

Figure 16 shows the resulting heatmap of the accessibility to the stroke centers currently established on household cluster level. The corresponding total patient outcomes at this moment are 4,171,839, which we use as baseline for the results of next section.

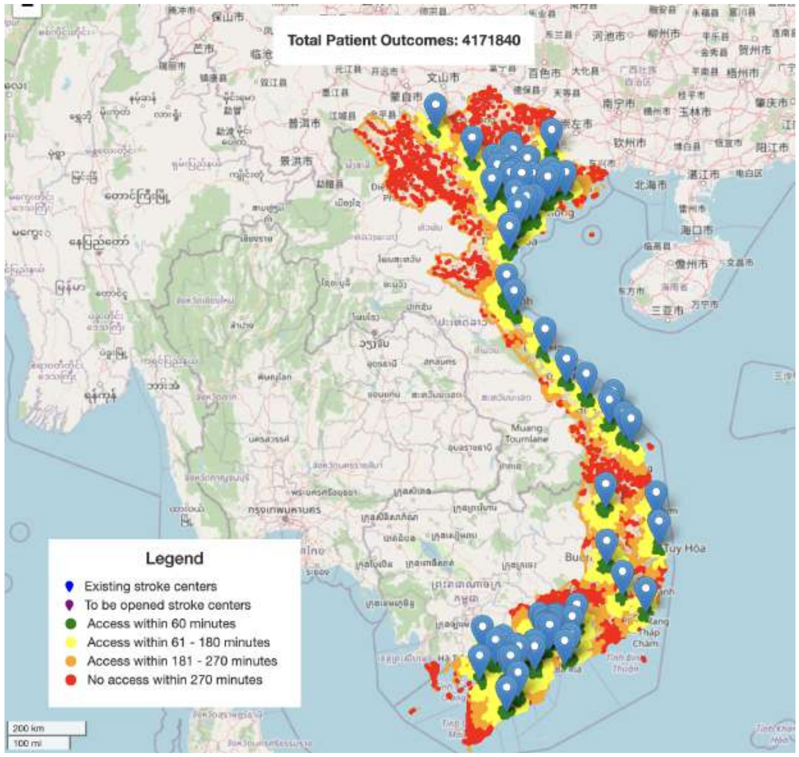

Figure 16: Heatmap of Accessibility with Current Stroke Centers in Vietnam

6.2 Results of Stroke Center Location Model in Vietnam

In this section, we start with exploring the model's scalability based on the runtimes of solving the stroke center location problem for Vietnam. Subsequently, we discuss the results of solving the stroke center location problem for Vietnam and compare them to the current situation outlined in Section 6.1. For this, we present a Pareto curve that illustrates the total patient outcomes and the accessibility in order to assess the impact of opening new stroke centers. Then, we further explore these findings by analyzing several budget scenarios for the maximum number of stroke centers that can be opened. Finally, we conduct a sensitivity analysis to evaluate the effect of average ambulance speed on total patient outcomes and accessibility in Vietnam.

6.2.1 Runtime and Scalability

Assessing the runtime of solving the optimization problem is essential to examine the model's scalibility, one of the key objectives of this thesis. Therefore, we calculate the runtime of solving the model on the tested country of this section to assess its performance. These tests are conducted using Google Colab Pro, a cloud-based Jupyter notebook environment provided by Google. The notebooks are configured to use a Python 3 runtime environment, running on an AMD EPYC 7B12 processor with 8 CPUs (each processor having 4 cores), operating at 2.25 GHz, and equipped with 51 GB of RAM. Moreover, the optimization model uses a Gurobi solver with an academic license.

The stroke center location problem for Vietnam optimizes approximately 121,000 decision variables, including 548 total stroke center locations (x_i) and 30,130 household clusters each considered across four travel time zones (y_{ij}). The Gurobi solver solves this problem within 30 to 32 seconds, irrespective of the budget. This relatively short runtime for this large scale model demonstrates that the model is computationally efficient and suitable for practical applications.

6.2.2 Pareto Curves

To analyze the results of the stroke center location problem, we re-run the model for various budgets and generate Pareto curves of the results. Figure 17 shows the Pareto curve for total patient outcomes against the number of opened stroke centers. This curve illustrates diminishing returns associated with opening additional stroke centers. The initial few stroke centers provide the most significant improvement in total patient outcomes, as they fill the most critical gaps in stroke care coverage. As more centers are added, the incremental benefits in total patient outcomes decrease because the remaining underserved areas have fewer patients or a less high stroke burden. This pattern highlights the importance of strategic placement of stroke centers to maximize the impact of each new facility. After opening roughly 100 new stroke centers, the total patient outcomes converges to the maximal achievable total patient outcomes of 4,508,610. Adding more centers after this point does not increase total patient outcomes anymore, since some inhabitants are not able to reach any of the (potential) stroke centers within 270 minutes, given they live in remote or isolated areas such as islands or mountains. In this case, resources can be better allocated to different aspects of stroke care.

Similarly, the Pareto curve in Figure 18 demonstrates the impact of the number of opened stroke centers on the population with access within the golden hour (60 minutes). For the first 20 newly opened stroke centers, the returns appear to follow a linear trend, indicating a steady improvement in golden hour access by opening new stroke centers. However, beyond this point, a trend of diminishing returns becomes evident. This means that each additional stroke center contributes progressively less to increasing the population's access within the golden hour. This pattern again underscores the importance of optimizing the location of new centers to maximize their impact before the benefits start to taper off. Notably is that the maximal achievable golden hour access with the potential facility location list remains at 64.8%, which is relatively low. This reflects that many inhabitants are not able to reach any of the (potential) stroke centers within an hour given, either because many inhabitants live in remote or isolated areas such as islands or mountains or due to the lack of sufficient hospitals in Vietnam.

Finally, Figure 19 illustrates the Pareto curves for population coverage across different travel time zones to stroke centers in Vietnam. Interestingly, if the budget increases, not only do total patient outcomes increase, but also so does the coverage for 60 minutes, 180 minutes, and 270 minutes. However, these curves indicate that while the population access increases with the opening of additional stroke centers, the rate of increase is relatively modest. These results are consistent with the detailed corresponding numbers presented in Table 22 of the Appendix. Initially, opening new centers significantly improves access, particularly in the most underserved regions. However, as more centers are established, the gains in coverage diminish, reflecting the principle of diminishing returns. This suggests that after a certain point, adding more stroke centers results in only marginal improvements in access, emphasizing again the need for strategic planning in locating new centers to ensure the most effective use of resources and to maximize the total patients benefit. Remarkably is that the population access within 60 minutes converge slower than the proportion of the population with access within 180 minutes, or within 270 minutes, and with no access within 270 minutes. This indicates that extending coverage within shorter travel times as the golden hour requires a larger number of new stroke centers than ensuring access within longer travel times (180 or 270 minutes) when optimizing total patient outcomes.

Summarizing, this analysis implies that opening additional stroke centers yields improved patient outcomes, but with a diminishing return in total patient outcomes. Therefore, opening the first few centers result in the highest impact, when strategically located in underserved, high stroke burden areas. Nonetheless, since Vietnam already has 106 stroke centers established, this impact is relatively low. Therefore, the additional gains by opening new centers using this model should be weighed against the investment costs. When opening more centers does not significantly increase total patient outcomes any more, resources might be better allocated to different aspects of stroke care, such as improving the existing stroke care centers or focusing on the prevention of strokes.

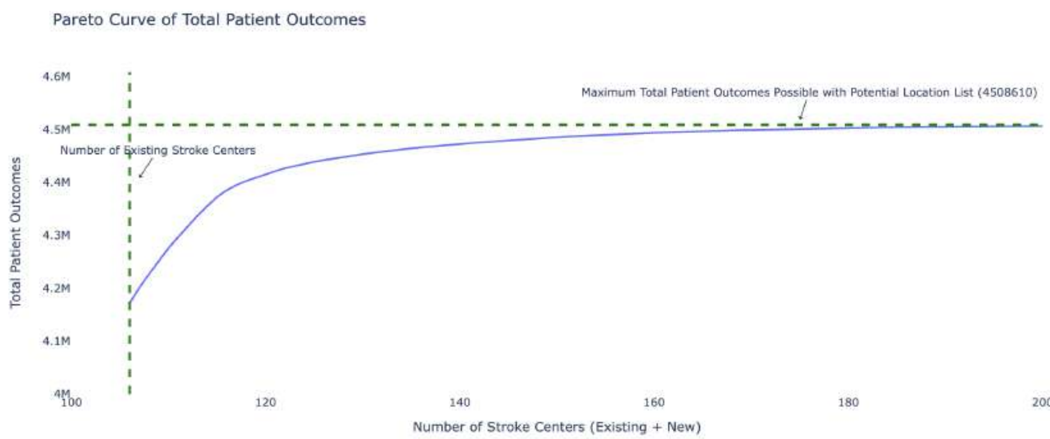

Figure 17: Pareto Curve of Total Patient Outcomes in Vietnam

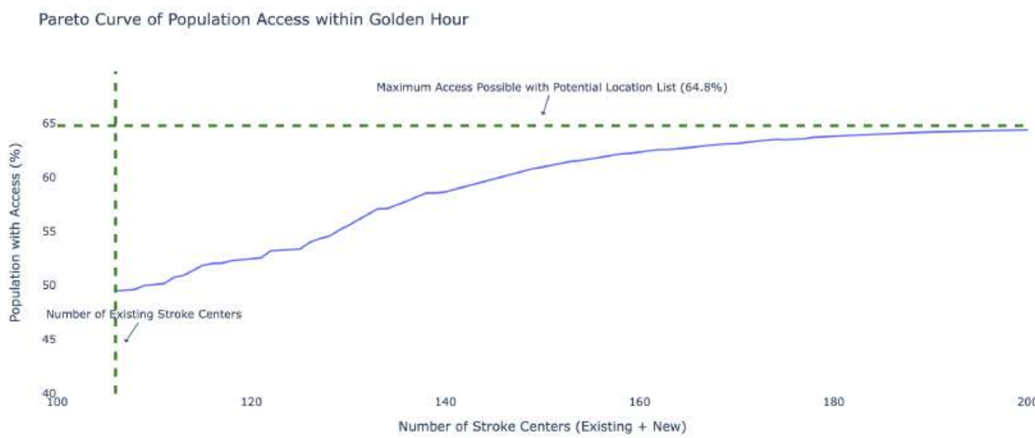

Figure 18: Pareto Curve of Population Access within Golden Hour (60 Minutes) in Vietnam

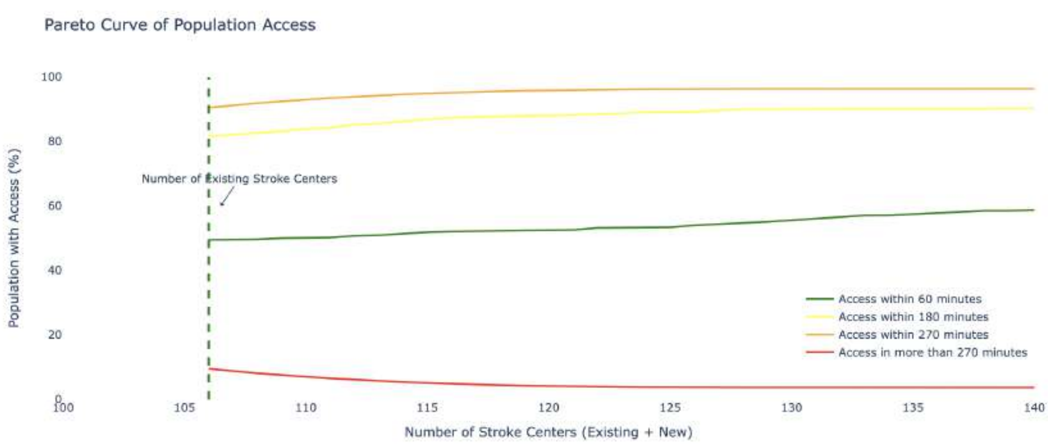

Figure 19: Pareto Curve of Population Access for each Travel Time Zone in Vietnam

6.2.3 Results for Various Fixed Budgets

To further evaluate the effectiveness of opening new stroke centers in improving stroke care, we examine the outcomes associated with several budgets in more detail. For this, we compare the current situation with scenarios involving the opening of one and five additional stroke centers.

The resulting optimal hospitals for new stroke centers under these scenarios are detailed in Table 14. This table displays the specific hospital locations appeared most effective for opening new stroke centers based on maximizing the total patient outcomes in the stroke center location problem.

	Hospital Names (b = 1)	**Hospital Names (b = 5)**
1	Trạm xá xã Đắk Ru	Trạm xá xã Đắk Ru
2		Khu Điều Trị
3		An Phước
4		Trung tâm ý tế xã Phú Thuận
5		thầy lang tuyển

Table 14: New Stroke Centers at Hospitals in Vietnam to be Opened

The impact on total patient outcomes and accessibility from opening these new stroke centers is quantified in Table 15. Here, insights are provided into how these new centers improve total patient outcomes and population access to timely stroke care.

	b = 0	**b = 1**	**b = 5**
Within 60 Minutes	49.5%	49.6%	50.2%
Within 180 Minutes	81.6%	82.1%	84.3%
Within 270 Minutes	90.5%	91.3%	93.5%
Over 270 Minutes	9.5%	8.7%	6.5%
Total Patient Outcomes	4,171,839	4,201,073	4,296,999

Table 15: Percentage of Population with Access to Stroke Centers in Vietnam for Different Budgets

Currently, 49.5% of the population has access to stroke care within the golden hour (60 minutes). A larger portion of the population, namely 81.6%, has access to stroke care within 3 hours, and 90.5% has access within 4.5 hours. However, there remains a fraction of 9.5% without timely access beneath 270 minutes.

Introducing one additional stroke center increases the total patient outcomes by 0.7%. The population with access within the golden hour increases by 0.1 percent point, raising it from the current level to 59.6%. Additionally, the coverage within 3 hours increases to 82.1%, and within 4.5 hours to 91.3%. Furthermore, the population without access within 4.5 hours decreases from 9.5% to 8.7%. This reduction indicates enhanced regional coverage and faster access to emergency care for a broader population segment by opening just one additional stroke center. Nonetheless, as the total patient outcomes have only increased by 0.7%, these additional gains should be weighed against its investments costs.

However, the introduction of five new centers boosts the total patient outcomes significantly by 3% compared to the current situation. Similarly, it increases the golden hour access to 50.2% of the population. Moreover, the population with access within 3 hours increases to 84.3%, and within 4.5 hours to 93.5%. These increases suggest that these additional centers effectively cover underserved areas with high stroke burdens. Moreover, the percentage of the population without access within

4.5 hours drops to 6.5%. This decrease highlights the strategic benefit of opening multiple centers to ensure rapid access to stroke care for at-risk populations, thereby improving total patient outcomes.

Figure 21 and Figure 22 at the end of this chapter substantiate this by visualizing the accessibility at the household cluster level and the locations of the existing and new stroke centers for both budgets.

6.2.4 Sensitivity Analysis of Average Ambulance Speed

To evaluate the impact of ambulance speed on the total patient outcomes and population access, we optimize the stroke center locations for a decreased average ambulance speed of 15 km/h and compare this to the results of a speed of 22 km/h.

Table 16 shows the optimal stroke centers resulting from solving the stroke center location problem using an average ambulance speed of 15 km/h. Remarkably, the optimal stroke center locations differ from the optimal locations when assuming an average ambulance speed of 22 km/h, as showed in Table 7. This trend holds true for both budget scenarios, which can be explained by the fact that lower average ambulance speeds increase travel times to stroke centers, resulting in reduced coverage areas. Consequently, the optimal locations that maximize total patient outcomes can differ based on varying population densities and demographics in these areas.

	Hospital Names (b = 1)	**Hospital Names (b = 5)**
1	Đa khoa Tín Đức	Đa khoa Tín Đức
2		An Phước
3		Trung tâm ý tế xã Phú Thuận
4		Trạm Y Tế Xã Phổ Thuận
5		Bệnh Viện Đa Khoa Quang Khởi

Table 16: New Stroke Centers at Hospitals in Vietnam to be Opened (b = 5, speed = 15 km/h)

As a result, also the households covered within different travel time zones, shown in Figure 23 and Figure 24 at the end of this chapter, deviate from the higher speed scenario. This again emphasizes the importance of using an accurately measured average ambulance speed when optimizing the locations of new stroke care centers.

Average Speed	**15 km/h**			**22 km/h**		
Budget	**b = 0**	**b = 1**	**b = 5**	**b = 0**	**b = 1**	**b = 5**
Within 60 Minutes	37.6%	38.3%	39.0%	49.5%	49.6%	50.2%
Within 180 Minutes	72.9%	73.8%	76.4%	81.6%	82.1%	84.3%
Within 270 Minutes	82.0%	83.0%	85.8%	90.5%	91.3%	93.5%
Over 270 Minutes	18.0%	17.0%	14.2%	9.5%	8.7%	6.5%
Total Patient Outcomes	3,749,327	3,792,966	3,918,993	4,171,839	4,201,073	4,296,999

Table 17: Population Coverage of Stroke Centers with Varying Average Ambulance Speed

From Table 17, it is evident that, as expected, the coverage and total patient outcomes significantly decrease with a decrease in average speed, while keeping the budget constant. However, opening more stroke centers in case of an ambulance speed of 15 km/h leads t slightly more pronounced percent point increases in coverage for each time zone compared to the scenario with a speed of 22 km/h. Similarly, the increases in total patient outcomes associated with opening stroke centers is more substantial at 15 km/h compared to 22 km/h. However, both total patient outcomes and population coverage within all different travel time zones are higher in case of a higher average ambulance speed, indicating that higher ambulance speeds yield better total patient outcomes.

In conclusion, the average ambulance speed should be accurately measured before policymakers use the model for optimizing the locations of new stroke care centers to maximize their impact, since the optimal locations depend on the average ambulance speed. Secondly, although lower average ambulance speeds pose challenges to achieving optimal stroke center coverage, they also highlight the significant benefits of expanding stroke care in case the average ambulance speed is lower in Vietnam. However, higher ambulance speeds substantially increase total patient outcomes and stroke care coverage for varying budgets and each travel time zone. This emphasizes the importance of an high ambulance speed as critical factor in improving overall patient outcomes in stroke care. Therefore, policymakers should strive for higher average ambulance speeds by lobbying for better infrastructure, investing in the quality of the ambulances, or train ambulance drivers to improve their driving skills.

6.3 Effectiveness Analysis of Current Stroke Centers in Vietnam

In this section we analyze the effectiveness of the current stroke centers in Vietnam by considering a greenfield approach. We start with the greenfield situation in which no stroke centers are opened at all. Then, we maximize the locations of new stroke centers using the stroke center location model, where the budget equals the number of currently existing stroke centers, and we again assume an average ambulance speed of 22 km/h. By comparing the model's results of the greenfield situation to the current stroke centers, we evaluate the effectiveness of the current stroke centers.

Figure 20 depicts the optimal stroke centers after optimizing the greenfield situation and the current stroke centers. We observe that 34 out of the 106 currently opened stroke centers are optimal as well in the solution of the greenfield approach. Looking at the plot, almost all other proposed optimal locations in the Greenfield situation are in close proximity to existing centers. Although the locations of these existing centers are close to their optimal locations, they are not strategically positioned to fully maximize their impact.

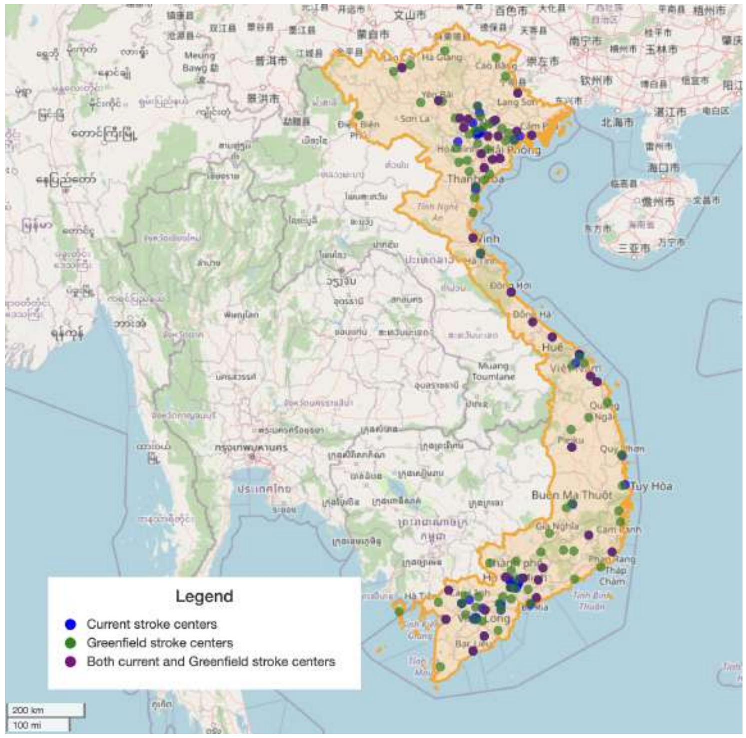

Figure 20: Current Centers and Optimal Centers in Greenfield Situation in Vietnam

This finding is substantiated by Table 18, illustrating that the population with access could be substantially higher when the current stroke centers were initially optimal located using the stroke center location model. Consequently, the overall patient outcomes could have been enhanced by 8% compared to the current locations, highlighting the critical need to strategically locate stroke centers using the model proposed in this thesis. Additionally, policymakers in Vietnam could consider closing existing centers and reopening them at the found optimal locations based on these results, if the increased benefits outweigh the associated additional costs of closing and opening these centers.

	Current	**Greenfield**
Within 60 Minutes	49.5%	62.0%
Within 180 Minutes	81.6%	91.0%
Within 270 Minutes	90.5%	96.4%
Over 270 Minutes	9.5%	3.6%
Total Patient Outcomes	4,171,839	4,492,389

Table 18: Coverage and Patient Outcomes of Current Situation versus Solution of Greenfield Situation

6.4 Comparison of Results with the Classical Healthcare Facility Location Model in Vietnam

This section evaluates the added value of the stroke center location model developed in this thesis. We first assess the added value of this model for Vietnam compared to the classical healthcare facility location approach, where only the golden hour coverage is maximized and no stroke risk factors are taken into account. Afterwards, we separately examine the contribution of incorporating different travel time zones and demographic risk factors for strokes, such as age, into our optimization problem. For all models, we assume an average ambulance speed of 22 km/h.

To assess the added value of the stroke center location problem developed in this thesis, we compare this model with the classical healthcare facility location model currently used in PISA. In this classical model, we optimize stroke center locations to maximize solely the golden hour coverage, and we neglect stroke risk factors. We can rewrite our model to the classical healthcare facility location model by setting the probability of a stroke constant for each age group, using a weighted average, and assigning weight only to the golden hour travel time zone in the objective function, using a NIH Stroke Scale of 42 for all other travel time zones to set their weights to zero. Note that the total patient outcomes must be computed manually thereafter, where we utilize the correct NIH Stroke Scale scores and stroke probabilities for accurately determining and comparing patient outcomes.

The results of the classical model and the model of this thesis are shown in Table 19. As expected, the population access within 60 minutes (the golden hour) increases significantly more for both budgets using the classical approach, where the objective is to maximize golden hour coverage. However, the population coverage within 180 minutes and within 270 minutes is substantially lower when using the classical approach compared to the model of this thesis. Consequently, more inhabitants lack timely access within 180 or within 270 minutes to a stroke center. Therefore, the total patient outcomes are reduced when using the classical approach compared to the stroke center location model of this thesis. In case of opening one additional stroke center, the total patient outcomes become 0.6% higher, using the model of this thesis compared to the classical model. Additionally, in case of opening five stroke centers, the total patient outcomes increase by 2.3% when using this thesis model instead of the classical approach. In summary, we can conclude that the stroke center location model of this thesis outperforms the classical healthcare facility location in terms of total patient outcomes in Vietnam and thereby enhances stroke care even further.

Facility Location Model	**Thesis**			**Classical**		
Budget	**b = 0**	**b = 1**	**b = 5**	**b = 0**	**b = 1**	**b = 5**
Within 60 Minutes	49.5%	49.6%	50.2%	49.5%	50.1%	52.3%
Within 180 Minutes	81.6%	82.1%	84.3%	81.6%	81.6%	83.3%
Within 270 Minutes	90.5%	91.3%	93.5%	90.5%	90.5%	91.2%
Over 270 Minutes	9.5%	8.7%	6.5%	9.5%	9.5%	8.8%
Total Patient Outcomes	4,171,839	4,201,073	4,296,999	4,171,839	4,175,109	4,198,445

Table 19: Comparison of the Stroke Center Location Model with the Classical Approach

To investigate this improvement in more detail, we separately examine the contribution of incorporating different travel time zones and demographic risk factors for strokes, such as age, into the optimization model solved for Vietnam. We evaluate the added value of optimizing different travel time zones by comparing the model of this thesis to a model with zero weights in the objective function for all travel time zones except the golden hour zone, using a NIH Stroke Scale of 42 for these zones. For assessing the added value of incorporating demographic stroke risk factors to account for population at-risk, we compare the model in this thesis with the same model where the probability on a stroke and the NIH Stroke Scale are held constant for both age groups, using weighted averages.

Remarkably, the findings of solving these models suggest that the solution for Vietnam, regardless of the budget, improves solely by optimizing different travel time zones, rather than focusing exclusively on the golden hour zone. Taking age into account as a stroke risk factor, however, does not contribute to better patient outcomes (or coverage) in Vietnam, as the model's solution remains unaffected by age incorporation. An explanation for this can be that the data for Vietnam suggest that the age distribution does not show significant differences across sub-regions in Vietnam. This observation aligns with findings that the percentage of people older than 80 years does not vary significantly (between 0.8% and 3.6%) across all household clusters throughout the entire country. Therefore, for Vietnam, the improvement of the model of this thesis, compared to the classical healthcare facility location model, is solely due to incorporating different travel time zones.

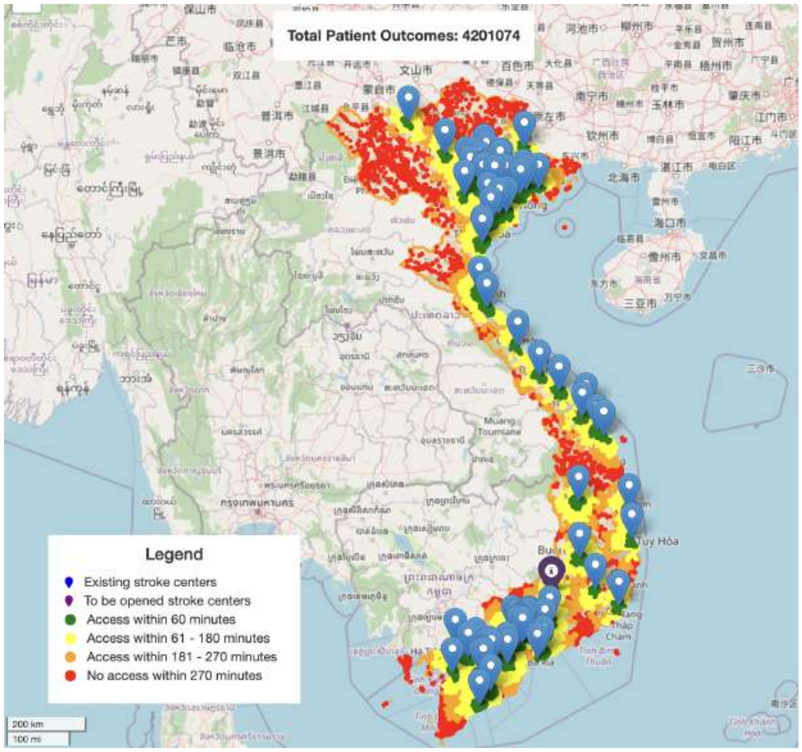

Figure 21: Heatmap of Accessibility with 1 New Stroke Centers in Vietnam (b = 1, speed = 22 km/h)

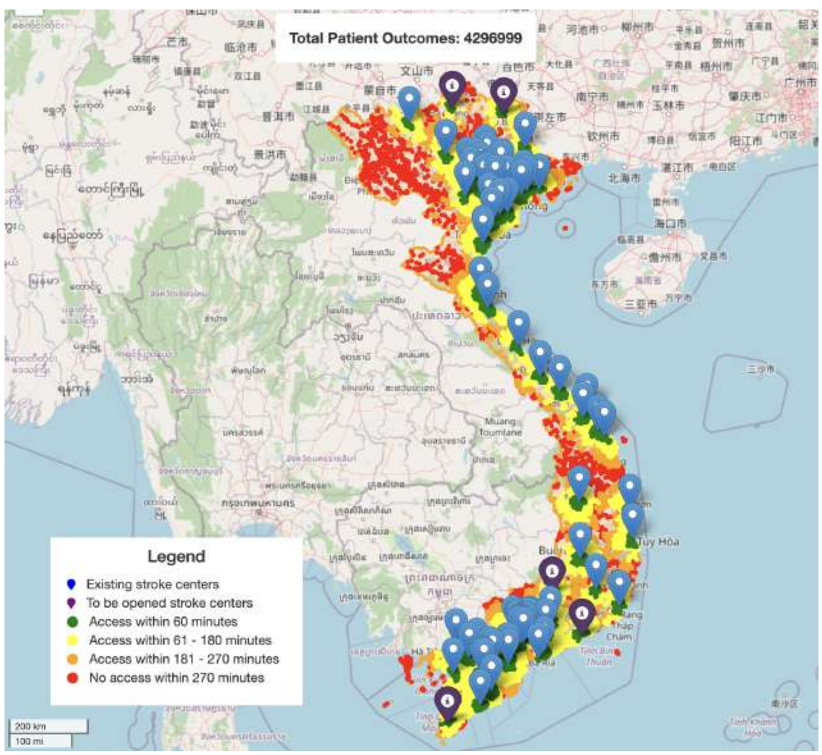

Figure 22: Heatmap of Accessibility with 5 New Stroke Centers in Vietnam (b = 5, speed = 22 km/h)

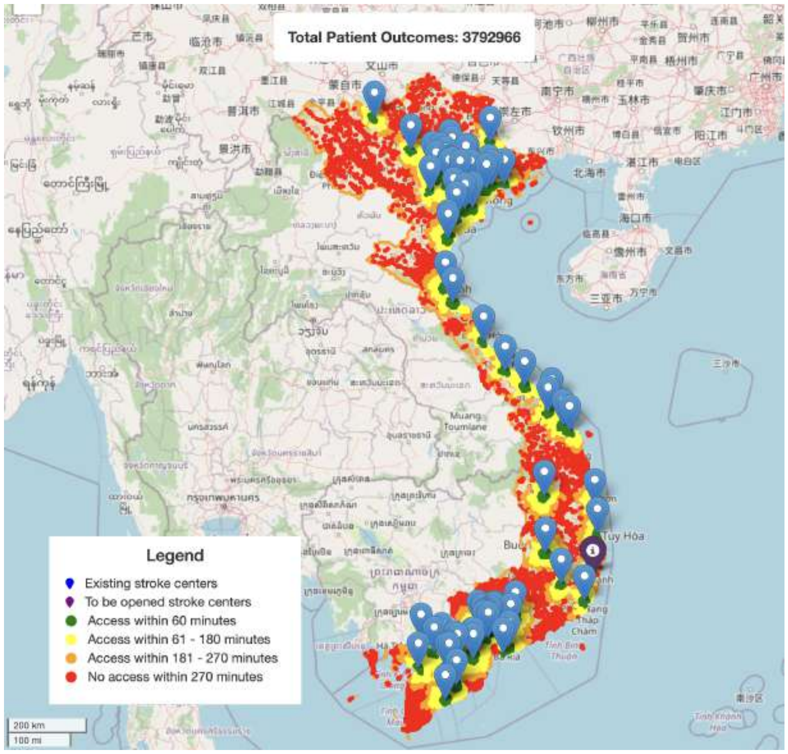

Figure 23: Heatmap of Accessibility with 1 New Stroke Centers in Vietnam (b = 1, speed = 15 km/h)

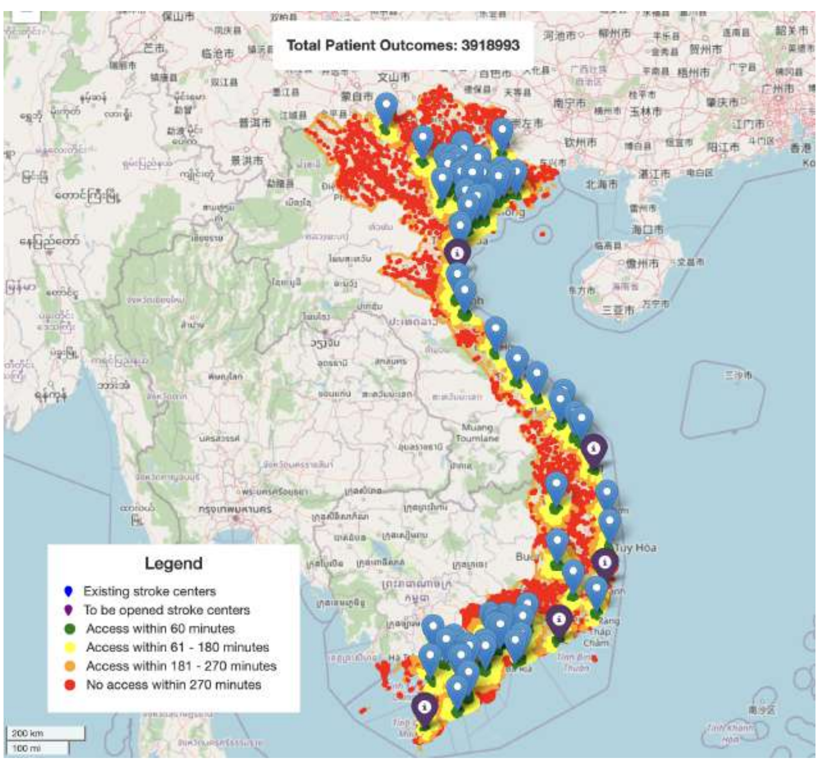

Figure 24: Heatmap of Accessibility with 5 New Stroke Centers in Vietnam (b = 5, speed = 15 km/h)

7 Comparative Analysis of Results from Tested Countries

In this section we perform a comparative analysis of the model's test results of Croatia and Vietnam to investigate whether the model is robust and adaptable to various context worldwide.

Both tested countries face a high stroke burden, as described in Section 4.1. At the same time, the countries have contrasting economic profiles. While Croatia is a high-income country, Vietnam is classified as lower-middle income. However, although Croatia has a higher income level, it also experiences a higher stroke probability than Vietnam, as given in Section 4.3. One explanation for this could be that high-income countries often have unhealthy lifestyles, including smoking, alcohol consumption, and obesity, which substantially increase the probability of stroke [1]. Even more remarkably is that even though the stroke incidence rate, stroke mortality rate, and the yearly probability of a stroke in Croatia is significantly higher than in Vietnam (Section 4.3), Croatia has twice as less stroke centers per inhabitants than Vietnam (Section 4.5), resulting in lower population coverage as well.

Therefore, it is not surprisingly that the test results for Croatia yield relatively higher total patient improvements than for Vietnam, as shown in Table 20. This table illustrates the percentage point change in coverage and total patient outcomes for both countries when opening one or five centers compared to the current situation ($b = 0$) of that country, assuming an average ambulance speed of 22 km/h. Looking at both budget scenarios, opening new stroke centers in Croatia results in substantially higher benefits in terms of total patient outcomes and population coverage for each time zone compared to its current situation than opening new centers in Vietnam. This is primarily because there are currently more underserved regions in Croatia with high stroke burden that could significantly benefit from opening stroke centers nearby. Nonetheless, even for Vietnam, the model shows significant improvements in total patient outcomes and coverage for all travel time zones when optimizing the locations of stroke centers.

Country	**Croatia**			**Vietnam**		
Budget	**b = 0**	**b = 1**	**b = 5**	**b = 0**	**b = 1**	**b = 5**
Within 60 Min.	20.3%	+ 5.7%pt.	+ 29.6%pt.	49.5%	+ 0.1%pt.	+ 0.7%pt.
Within 180 Min.	73.0%	+ 7.9%pt.	+ 20.3%pt.	81.6%	+ 0.5%pt.	+ 2.7%pt.
Within 270 Min.	93.7%	+ 1.9%pt.	+ 4.3%pt.	90.5%	+ 0.8%pt.	+ 3.0%pt.
Over 270 Min.	6.4%	− 2.0%pt.	− 4.4%pt.	9.5%	− 0.8%pt.	− 3.0%pt.
Patient Outcomes	293,051	+ 3.3%	+ 9.5%	4,171,839	+ 0.7%	+ 3.0%

Table 20: Results of Opening Centers Relative to Current Situation in Croatia and Vietnam

Concluding, the potential improvement by utilizing the stroke center location model for both contrasting countries is significant. For a country with a few stroke centers but a high stroke burden, the model emphasizes the crucial importance for opening stroke centers. By using the model, the locations of these centers can be identified such that they yield the highest benefit in total patient outcomes. But also for high-income countries, the model can help policymakers in making informed decision on the allocation of resources for stroke care. The tests showed that even for a country with already more established stroke centers, optimal locating stroke centers can improve patient outcomes significantly, making the model robust and adaptable. However, as these benefits are relatively lower here, policymakers can use this model to balance the investments costs of opening new centers against these increased benefits, and consider allocating resources to other aspects of stroke care as improving existing stroke care or focusing on prevention campaigns.

8 Conclusion

This thesis aimed to develop a scalable and adaptable solution for enhancing stroke care accessibility worldwide by creating a model for optimizing the locations of new stroke centers in relation to at-risk populations, with the goal of enhancing access and reducing treatment initiation times of acute ischemic stroke, ultimately improving total stroke patient outcomes. By testing the model on a high-income country and a low-income country, both facing high stroke burdens, a broad range of challenges has been investigated to ensure robustness of the model. In Section 8.1, we draw conclusions from these tests by summarizing the key results and their implications. Thereafter, we discuss limitations of this study in Section 8.2. We conclude by suggesting some future research directions in Section 8.3.

8.1 Findings and Implications

The goal of this thesis was to develop a scalable and adaptable model to improve total stroke patient outcomes by optimizing the locations of new stroke centers in relation to at-risk populations. Therefore, we developed an stroke center location model that extends the classical healthcare facility location model by integrating different travel time zones and demographic risk factors, such as age.

Our main finding is that the developed stroke center location model significantly enhances total patient outcomes, outperforming the classical healthcare facility location model. The model provides valuable insights for policymakers in making strategic decisions on resource allocation for stroke care. After testing the model on both high-income country Croatia and low-income country Vietnam, it is evident that the model is scalable and adaptable to various national contexts worldwide.

The improved performance of the stroke center location, compared to the classical healthcare facility location model , is primarily due to the inclusion of various stroke treatment windows or travel time zones into the optimization model. Taking age into account as stroke risk factor in the tested countries, however, does not yet contribute to improved patient outcomes, as the model's solution for these tests remains unaffected by age incorporation. An explanation for this is that the age distribution does not significantly differ across sub-regions in both tested countries. Nonetheless, this approach still holds great potential to improve the model's outcomes in countries with significant geographical differences in demographics, but further research is needed for this.

The established performance of the model is supported by the Pareto curves resulting from the real-life test cases. These curves reveal crucial insights into optimizing healthcare infrastructure for stroke care by depicting total patient outcomes and population coverage through the opening of new stroke centers. They demonstrate that while opening new stroke centers initially leads to substantial improvements in total patient outcomes and population coverage, these benefits diminish as additional centers are added. Therefore, opening the first few stroke centers yields the highest increase in total patient outcomes, provided they are located in areas that will have the greatest impact, particularly in underserved areas facing a high stroke burden. An in-dept analysis of various budget scenarios confirms that even limited investments in new stroke centers can significantly enhance accessibility by opening only a few stroke centers at optimal locations. This emphasizes the crucial need of strategically locating new stroke centers to maximize their impact on overall patient benefits, in which this model can empower policymakers by making such strategic decisions. However, the observed diminishing returns imply that beyond a certain number of newly opened stroke centers, the incremental benefits diminish. Therefore, once the model indicates that this threshold is reached, policymakers should consider reallocating resources to alternative strategies aimed at enhancing patient outcomes and coverage, such as improving existing facilities or preventing strokes by community health education. Lastly, applying a greenfield approach to the model can provide valuable insights into the effectiveness of the current stroke center locations. If the model's solution for the greenfield scenario indicates that the current placement of stroke centers is not optimal for maximizing patient outcomes, policymakers should consider whether the improved patient outcomes from relocating these centers to more strategic locations outweigh the associated costs. In conclusion, the model offers valuable insights into the optimal locations for new stroke centers and their associated benefits, enabling policymakers to make informed trade-offs between establishing new centers and allocating resources to different aspects of stroke care or prevention. Implementing this model can therefore lead to a more efficient allocation of resources and better stroke care planning, ultimately improving total patient outcomes related to stroke care.

To ensure the effectiveness of the model, it is crucial to consider ambulance speed as a key factor in identifying optimal stroke center locations to maximize patient outcomes. Not only do the optimal locations depend on the magnitude of the average ambulance speeds, but higher speeds also correlate with improved total patient outcomes. Therefore, policymakers must consider ambulance speed as crucial factor in healthcare planning. Firstly, they should strive to increase the average ambulance speed to improve total patient outcomes, which can be done for example by lobbying for better infrastructure, investing in the quality of the ambulances, or train ambulance drivers to improve their driving skills. Secondly, when using the model for identifying stroke center locations, it is crucial for policymakers to use precise speed measures, as this parameter affects the optimal locations and thereby the total patient outcomes. By establishing these two aspects, the model effectively supports policymakers in achieving both efficient resource allocation and enhanced patient outcomes.

In addition to the effective outcome of the model, the model's scalability is another key objective of this thesis. The comparison of runtimes between solving the stroke center location problem for the tested countries indicates that the model exhibits reasonable scalability. Specifically, the runtime increases from 8-10 seconds for approximately 90,000 decision variables (Croatia) to 30-32 seconds for approximately 120,000 decision variables (Vietnam). This suggests that while the model's runtime does increase with the number of decision variables, the runtime increase is roughly proportional to the increase in the number of decision variables, demonstrating that the model can handle larger datasets within an increased, but acceptable time frame. Therefore, the model is scalable and remains practical for larger and more complex datasets.

Since the model is scalable and adaptable, policymakers could also gain valuable insights into addressing broader location-based challenges using the model with minor adjustments. These may include determining optimal sites for new schools in developing countries, the placement of prevention campaigns, deploying mobile vaccination units, and identifying suitable locations for emergency shelters, fire stations, police stations, or other (emergency) medical services.

Additionally, a promising feature of the stroke center location model involves extending the used approach to broader implementations of facility location problems, including nonlinear ones. Traditional facility location problems that aim to minimize distance face restrictions in size due to the requirement of a double index. However, by incorporating travel time zones into the mathematical formulation, as demonstrated in this thesis, these limitations can be overcome. This approach entails calculating the number of inhabitants covered within each travel time zone and multiplying it by the average distance of the zone to estimate the total weighted distance. Using this total weighted distance metric, the model can now effectively minimize distance without the need for a double index, thereby significantly increasing the problem's scalability and complexity that can be addressed.

8.2 Limitations

Although the developed model has proven to be effective in enhancing stroke care, this study is not without limitations.

Average Ambulance Speed

Most importantly, the model assumes static ambulance travel speeds across all hospital facilities throughout the entire country. Thereby, it does not account for potential geographical variations due to traffic conditions, geographic obstacles, infrastructure conditions, or differences in emergency response capabilities. Since the optimal locations of stroke centers depend on the average ambulance speed, the solution might deviate when using a more realistic approach that considers distinct average ambulance speeds for each hospital facility.

Another limitation of the model concerning the average ambulance speed is the maximum distance constraint imposed by the Mapbox API. This tool restricts us to only generate isochrones with a maximum radius of 100 km, corresponding to a maximum average ambulance round-trip speed of 22.2 km/h. Considering that precise average ambulance speeds are crucial for optimizing stroke center locations, a fixed upper bound of 22.2 km/h could limit the accuracy of the model. To mitigate this issue, one potential solution is to set up OpenRouteService locally. Although this approach requires a high amount of RAM on a local machine to ensure efficient processing, it enables more accurate calculations of the travel times to stroke centers, thereby improving the model's reliability and effectiveness.

Data Accuracy

This thesis leverages the power of open-source data and tools, such that the model can be applied to other country. However, this data is not always accurate, especially in developing countries where data collection is less of a priority. This might result in incomplete datasets which are not completely representative for the real situation.

One of the used data tools facing this problem is the Overpass API of OpenStreetMap, which we used for extracting existing hospitals as potential stroke care locations. The curated lists of existing stroke centers for both Croatia and Vietnam contained hospitals that were not present in the extracted existing hospitals by the Overpass API, indicating the incompleteness of the data collected by the Overpass API.

For the stroke center location model to achieve its desired outcome, it is essential that the data closely reflects real-world conditions. Therefore, users of this model are encouraged to actively participate in data collection in (developing) countries. Additionally, it is important to re-run the model before basing strategical decisions on it, as data sources might be updated over time. High-quality, up-to-date data enhances the accuracy of this stroke center location problem, ultimately maximizing the benefits for the population.

Scalability

Lastly, the goal of this thesis was to create a scalable model to enhance stroke care worldwide. This goal has been achieved as the model is scalable and adaptable to different national contexts. The optimization process for the tested countries runs in just ten of seconds, making the model efficient enough to be used as an interactive tool where budgets can be easily adjusted. However, if the number of potential locations increases to around 10,000, the runtime for solving the problem will increase as well. It is reasonable to predict that the issue can still be resolved within an hour, but further research is needed for this. This increase in runtime is even more significant when the number of household clusters increases, since each household is considered across four travel time zones, which could result in predicted runtimes of a few tens of minutes to a few hours when solving the stroke center location problem. By clustering these household into larger clusters of 5 kilometers by 5 kilometers, the runtime increase will be less substantial. In this way, the model remains scalable and useful for practical applications globally.

Nonetheless, it is essential to highlight that the preprocessing of the data itself, where the average ambulance speed is set, is a more time-intensive process taking from tens of minutes up to a few hours. While this step can be performed in advance for all countries to prevent the need for re-running the model each time and to ensure scalability, adjusting the average ambulance speed necessitates significant time investment. This further underscores the necessity of using an accurate ambulance speed to avoid the need for adjustments later.

Despite these limitations, the model offers valuable insights for policymakers in making strategic decisions about stroke care, contributing to reduced mortality and long-term disability associated with strokes.

8.3 Future Directions

Given the effective outcomes of the model and its associated limitations, several future research steps could be taken to refine and enhance the stroke center location model developed in this thesis. These future directions can be categorized into enhancing and expanding the model.

Enhancing the Stroke Center Location Model

The stroke center model can be enhanced in several ways to further improve its performance. An important initial step is to further investigate the added value of incorporating stroke risk factors into the model for identifying population at-risk, as the countries tested in this thesis have not yet provided sufficient evidence for this. A more detailed evaluation of the contribution of age as demographic risk factor to the model's outcomes could involve testing the stroke center location model in countries with more geographical variations in demographics than the currently tested countries. Moreover, the integration of additional stroke risk factors in the model could be explored in order to test and enhance the model's effectiveness in identifying and prioritizing population at-risk. For this, other demographic risk factors, such as gender and ethnicity, as well as behavioral risk factors, can be easily incorporated into the model with only minor modifications. These adjustments could potentially enhance the model's effectiveness and are therefore interesting feature research directions.

Another promising improvement of the model is the implementation of geographical variations in average ambulance speed. Hence, future research directions could include integrating different average ambulance speed specific for each hospital, based on ambulance data. This enhancement has the potential to significantly improve the accuracy of the model, leading to a more reliable and effective model for optimizing stroke care locations.

In line with this, another potential improvement concerns the model's assumption that patients immediately recognize the emergency upon symptom onset and, therefore, do not delay seeking medical help. As this assumptions might not be realistic, incorporating this delayed response in the average ambulance speed makes the model more realistic and accurate.

The assumption that all stroke centers have unlimited patient capacity and unlimited specialized medical staff available might not be realistic as well. Additionally, it might be the case that not all hospitals offer the same level of stroke care. Adjusting the model by implementing patient and staff capacity constraints could further improve the model.

Lastly, an interesting observations from the obtained Pareto curves in both test cases, is that when the budget increases, not only the total patient outcome increases as well, but so does the coverage for 60 minutes, 180 minutes, and 270 minutes. In further research it can be investigated whether this could be mathematically proven, using the mathematical formulation of the stroke center location problem. Such an investigation could enhance the model's effectiveness by providing a clearer understanding of how budget impacts patient outcomes and coverage. This insight would enable policymakers to make more informed decisions about resource allocation for stroke centers.

Extending the Stoke Center Location Model

Since the current model has already proven to be effective, there are several promising extensions that could be explored. Firstly, it could be insightful to modify the model's outcome so that it also provides the expected number of stroke patients for each optimal stroke center. This way, stroke centers can adjust their capacity based on the anticipated number of stroke patients they are likely to encounter.

Furthermore, as this thesis only focused on ischemic strokes, accounting for 87% of all strokes, it might be interesting to investigate whether the results also hold for hemorrhagic stroke that accounts for 13% of all strokes. If this is not the case, the model could be improved by incorporating hemorrhagic strokes to determine the optimal locations of stroke centers for all stroke types relative to their occurrence.

A last promising future research direction involves the extension of the approach of the stroke center location model to broader facility location problems, including nonlinear ones. As explained in Section 8.1, using different travel zones as discretization of the travel distance, a facility location model can effectively minimize this distance estimate without the need for a double index. By applying a single index, the number of parameters in the model decreases drastically, thereby increasing the model's capability of handling larger scale models. Future research could explore these implementations further and assess their impact on handling larger problem sizes.

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9 Appendix

A Assessment of NIH Stroke Scale

2706

Providence | Health System

NIH STROKE SCALE

PSVMC - Providence St. Vincent Medical Center
PMH - Providence Milwaukie Hospital
PPMC - Providence Portland Medical Center

PATIENT IMPRINT

Category	Score/Description		Date/Time Initials	Date/Time Initials	Date/Time Initials	Date/Time Initials	Date/Time Initials
1a. Level of Consciousness (Alert, drowsy, etc.)	0 = Alert 1 = Drowsy 2 = Stuporous 3 = Coma						
1b. LOC Questions (Month, age)	0 = Answers both correctly 1 = Answers one correctly 2 = Incorrect						
1c. LOC Commands (Open/close eyes, make fist/let go)	0 = Obeys both correctly 1 = Obeys one correctly 2 = Incorrect						
2. Best Gaze (Eyes open - patient follows examiner's finger or face)	0 = Normal 1 = Partial gaze palsy 2 = Forced deviation						
3. Visual Fields (Introduce visual stimulus/threat to pt's visual field quadrants)	0 = No visual loss 1 = Partial Hemianopia 2 = Complete Hemianopia 3 = Bilateral Hemianopia (Blind)						
4. Facial Paresis (Show teeth, raise eyebrows and squeeze eyes shut)	0 = Normal 1 = Minor 2 = Partial 3 = Complete						
5a. Motor Arm - Left **5b. Motor Arm - Right** (Elevate arm to 90° if patient is sitting, 45° if supine)	0 = No drift 1 = Drift 2 = Can't resist gravity 3 = No effort against gravity 4 = No movement X = Untestable (Joint fusion or limb amp)	Left					
		Right					
6a. Motor Leg - Left **6b. Motor Leg - Right** (Elevate leg 30° with patient supine)	0 = No drift 1 = Drift 2 = Can't resist gravity 3 = No effort against gravity 4 = No movement X = Untestable (Joint fusion or limb amp)	Left					
		Right					
7. Limb Ataxia (Finger-nose, heel down shin)	0 = No ataxia 1 = Present in one limb 2 = Present in two limbs						
8. Sensory (Pin prick to face, arm, trunk, and leg - compare side to side)	0 = Normal 1 = Partial loss 2 = Severe loss						
9. Best Language (Name item, describe a picture and read sentences)	0 = No aphasia 1 = Mild to moderate aphasia 2 = Severe aphasia 3 = Mute						
10. Dysarthria (Evaluate speech clarity by patient repeating listed words)	0 = Normal articulation 1 = Mild to moderate slurring of words 2 = Near to unintelligable or worse X = Intubated or other physical barrier						
11. Extinction and Inattention (Use information from prior testing to identify neglect or double simultaneous stimuli testing)	0 = No neglect 1 = Partial neglect 2 = Complete neglect						
	TOTAL SCORE						

INITIAL	SIGNATURE	INITIAL	SIGNATURE	INITIAL	SIGNATURE

155337 '004

Figure 25: Assessment of NIH Stroke Scale according to Kwah et al. [11]

B Detailed Results of Tested Model in Croatia

Number of New Stroke Centers	Total Patient Outcomes	Access within 60 Minutes	Access within 180 Minutes	Access within 270 Minutes	No Access in 270 Minutes
0	293,051	20.3%	73.0%	93.7%	6.3%
1	302,810	26.0%	80.9%	95.6%	4.4%
2	312,492	46.7%	88.1%	95.9%	4.1%
3	316,140	49.1%	91.1%	96.6%	3.4%
4	318,831	49.9%	92.3%	97.4%	2.6%
5	320,918	49.9%	93.3%	98.0%	2.0%
6	322,460	53.5%	94.5%	98.0%	2.0%
7	323,594	54.6%	94.7%	98.3%	1.7%
8	324,711	55.9%	95.6%	98.4%	1.6%
9	325,631	56.1%	95.9%	98.6%	1.4%
10	326,508	58.5%	96.0%	98.6%	1.4%
11	327,231	58.7%	96.3%	98.8%	1.2%
12	327,940	60.7%	96.3%	98.8%	1.2%
13	329,280	62.7%	96.3%	98.8%	1.2%
14	329,280	62.9%	96.5%	99.0%	1.0%
15	329,807	64.3%	96.5%	99.0%	1.0%
16	330,260	65.1%	97.2%	99.0%	1.0%
17	330,681	66.3%	97.3%	99.0%	1.0%
18	331,085	67.4%	97.3%	99.0%	1.0%
19	331,485	68.4%	97.5%	99.0%	1.0%
20	331,795	68.9%	98.0%	99.0%	1.0%
...	...	...	...	...	...
141	335,454	78.4%	98.6%	99.0%	1.0%

Table 21: Patient Outcomes and Population Access for Varying Budgets in Croatia (Speed = 22 km/h)

C Detailed Results of Tested Model in Vietnam

Number of New Stroke Centers	Total Patient Outcomes	Access within 60 Minutes	Access within 180 Minutes	Access within 270 Minutes	No Access in 270 Minutes
0	4,171,839	49.5%	81.6%	90.5%	9.5%
1	4,201,073	49.6%	82.1%	91.3%	8.7%
2	4,226,781	49.6%	82.4%	91.9%	8.1%
3	4,252,033	50.0%	83.2%	92.5%	7.5%
4	4,275,795	50.0%	83.9%	92.0%	7.0%
5	4,296,999	50.2%	84.3%	93.5%	6.5%
6	4,317,196	50.7%	85.3%	98.9%	6.1%
7	4,337,290	50.9%	85.6%	94.3%	5.7%
8	4,355,209	51.4%	86.2%	95.6%	5.4%
9	4,372,617	51.9%	86.9%	94.9%	5.1%
10	4,385,524	52.0%	97.4%	95.2%	4.8%
11	4,394,940	52.1%	87.6%	95.5%	4.5%
12	4,402,598	52.3%	87.9%	95.6%	4.4%
13	4,409,076	52.4%	87.9%	95.8%	4.2%
14	4,415,476	52.4%	88.1%	95.9%	4.1%
15	4,421,225	52.6%	88.3%	96.0%	4.0%
16	4,426,777	53.2%	88.6%	96.1%	3.9%
17	4,431,047	53.3%	88.7%	96.2%	3.8%
18	4,434,981	53.3%	89.1%	96.2%	3.8%
19	4,438,879	53.4%	89.2%	96.3%	3.7%
20	4,442,149	54.0%	89.2%	96.3%	3.7%
...	...	...	...	...	...
442	4,508,610	64.8%	91.5%	96.5%	3.5%

Table 22: Patient Outcomes and Population Access for Varying Budgets in Vietnam (Speed = 22 km/h)