APPLICATION OF DATA ENVELOPMENT ANALYSIS TO OPTIMIZE TRANSFER OF ISCHEMIC STROKE PATIENTS FOR ENDOVASCULAR THROMBECTOMY

by

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Submitted in partial fulfilment of the requirements
for the degree of Masters of Applied Science

at

Dalhousie University
Halifax, Nova Scotia
December 2023

Dalhousie University is located in Mi'kma'ki,
the ancestral and unceded territory of the Mi'kmaq.
We are all Treaty people.

TABLE OF CONTENTS

List of Tables

List of Figures

Abstract

Stroke is a leading cause of disability and death. A new treatment called Endovascular Thrombectomy (EVT) is available to severe stroke patients, but it is only offered at large urban centres and its effectiveness is time dependant. Patients from Primary Stroke Centres (PSCs) must be transferred quickly. Many patients that are transferred are deemed ineligible for treatment upon arrival. Data from Nova Scotia was obtained for three years. This comprehensive analysis of patients transferred for EVT with PSCs as distinct Decision-Making Units (DMUs) was conducted. Input data included patient demographics, system efficiency, imaging interpretation, and distance between hospitals. The output was whether EVT was performed. Data Envelopment Analysis (DEA) was used to determine efficiency scores for the PSCs. After applying DEA, the study revealed variations in productivity change among different PSCs. The results highlighted the negative effect of considerable distances between certain PSC and the Comprehensive Stroke Centre (CSC).

LIST OF ABBREVIATIONS USED

- ADD: Additive Model
- AHP: Analytic Hierarchy Process
- AMI: Acute Myocardial Infarction
- ANN: Artificial Neural Network
- ASPECTS : Alberta Stroke Program Early CT Score
- AT: Access Time
- BCC: Banker, Charnes, and Cooper
- BI: Barthel Index
- CCR: Charnes, Cooper, and Rhodes
- CMUs: Clinical Management Units
- CSC: Comprehensive Stroke Centre
- CRS: Constant Return to Scale
- CT: Computed Tomography
- CTA: CT Angiogram
- CTP: CT perfusion
- DEMATEL: Decision Making Trial and Evaluation Laboratory
- DRS: Decreasing Return to Scale
- DIDO: Door-In-Door-Out time
- DM: Decision-Maker
- DEA: Data Envelopment Analysis
- DES: Discrete Event Simulation
- DMUs: Decision Making Units
- DOE: Design of Experiment
- DRG: Diagnosis-Related Group
- EDs: Emergency Departments
- EMS: Emergency Medical Services
- ESCAPE: Endovascular Treatment Compared to Conventional treatment for Patients with Acute Ischemic Stroke
- EVT: Endovascular Thrombectomy
- FTE: Full Time Equivalent
- GDEA: Generalized DEA
- GDP: Gross Domestic Product
- HCN: Health Card Numbers
- HCQI: Health Care Quality Indicators

- HT: Healthcare Time
- HTP: Health Transformation Programs
- IO: Input-Oriented
- IRS: Increasing Return to Scale
- LOS: Length of Stay
- LVO: Large Vessel Occlusion
- mCTA: multiphase CTA
- MCDA: Multi Criteria Decision Analysis
- MI: Myocardial Infarction
- MOLP: Multi-Objective Linear Programming
- MPI: Malmquist Productivity Index
- MPS: Most Preferred Solution
- MRI: Magnetic Resonance Imaging
- NCCT: Non-Contrast Computed Tomography
- NINDS: National Institute of Neurological Disorders and Stroke
- NNT: Number Needed to Treat
- OECD: Organization for Economic Co-operation and Development
- OO: Output-Oriented
- OR: Operations Research
- OT: Occupational Therapy
- OTE: Overall Technical Efficiency
- PCI: Percutaneous Coronary Intervention
- PEC: Pure Efficiency Change
- PIM-DEA: Probability-Imprecise DEA
- PHC: Primary Health Care
- PPE: Personal Protective Equipment
- PSC: Primary Stroke Centers
- PT: Physical Therapy
- PTE: Pure Technical Efficiency
- RTS: Return to Scale
- SBM: Slack-Based Measurement
- SDEA: Stochastic Data Envelopment Analysis
- SE: Scale Efficiency
- SEC: Scale Efficiency Change
- STEM: Step Method
- TC: Total Cost efficiency
- TE: Technical Efficiency
- TFPG: Total Factor Productivity Growth

- TFP: Total Factor Productivity
- TNK: Tenecteplase
- tPA: Tissue Plasminogen Activator
- VRS: Variable Return to Scale

CHAPTER 1 INTRODUCTION

Data Envelopment Analysis (DEA) is a method of measuring productivity to assess multiple dimensions of productivity. DEA uses a concept called technical efficiency, which examines the relationships between various inputs and the related output. This allows different hospital setting to have different inputs that will yield the optimal output. This concept incorporates efficiency and effectiveness.

The application of DEA in stroke care services within the healthcare industry holds significant potential. DEA, a quantitative method for evaluating efficiency by comparing inputs (resources) and outputs (services), can be instrumental in assessing and optimizing resource utilization in stroke care. By using DEA, there is an opportunity to standardize health service delivery, benchmark the proportion of stroke patients receiving timely treatment, and enhance the overall management and efficiency of stroke care. This approach aims to ensure that treatments for acute ischemic stroke, for example, are delivered optimally across different healthcare centres regardless of differences in the populations that they serve and the size of their centre.

In healthcare, DEA can be applied to assess and optimize the performance of healthcare facilities, such as hospitals, in terms of resource utilization and service delivery. In the context of stroke care, DEA can be used to assess the efficiency of hospitals in providing EVT, considering factors like patient throughput, resource allocation, and quality of care. This emphasizes the need for tools like DEA to assess and optimize the performance of healthcare facilities, ensuring they can deliver essential services efficiently. DEA can help identify areas for improvement in resource allocation and policy formulation, ultimately enhancing stroke care and other critical healthcare services.

Stroke is a significant burden worldwide. In Canada, stroke ranks as the leading cause of adult disability (1), and it is a leading cause of death (2). During an average lifetime, every Canadian will be touched by a stroke by either becoming a victim of this disease or a close family member having a stroke. Nova Scotia’s older population is more affected by stroke; consequently, Nova Scotia has a higher incidence of stroke than other Canadian provinces, with 140 strokes annually per 100,000 people compared to 113-116 stroke incidences per 100,000 people in provinces outside of Atlantic Canada (3). Moreover, stroke affects older people more than younger adults, as the average stroke incidence is 69 years old (4). The odds of having a stroke increases with age: Stroke is anticipated to affect 10% of Canadians aged 65 years or older, with the likelihood increasing to 20% among Canadians aged 85 years or older (2).

The most common type of stroke is ischemic stroke, constituting approximately 85% of all strokes. Fortunately, acute ischemic stroke can be treatable with a medical treatment called thrombolysis with either alteplase (also called tissue Plasminogen Activator (tPA)) or Tenecteplase (TNK). The key randomized controlled trial (RCT), the National Institute of Neurological Disorders and Stroke (NINDS) trial, found that 39% of patients treated with alteplase will experience no disability, in contrast to 26% of untreated patients (5). Around 20% of patients with ischemic stroke can be suitably treated with alteplase. As a result, thrombolysis treatment is widely available at hospitals equipped with a Computed Tomography (CT) scanner and possessing the necessary expertise to manage stroke patients. In Nova Scotia, there are ten hospitals across the province that provide thrombolysis treatment, hence they are called Primary Stroke Centres (PSC), and paramedics are trained to bypass a closer hospital to bring suspected acute stroke patients to a PSC. In 2015, a series of RCTs (6), including the Canadian-led ESCAPE trial (7), proved a new treatment for ischemic stroke patients to be highly efficacious: Endovascular Thrombectomy (EVT). This treatment mechanically removes the clot using stent retriever devices and/or aspiration (8).

EVT is provided to patients with a Large Vessel Occlusion (LVO), which is the most severe form of ischemic stroke; approximately 30-40% of all ischemic stroke is because of an LVO (9). EVT is highly effective; About 26.9% of stroke patients treated with EVT will achieve recovery without disability, in contrast to 12.9% of patients who did not undergo EVT. Additionally, 46.0% of EVT-treated patients will experience only minor disability, compared to 26.5% of patients who did not receive EVT (6). This results in a Number Needed to Treat (NNT) for a reduction in disability of 2.6 (10). Note that patients in the control group of the EVT trials (patients that did not receive EVT) may have received alteplase. Yet, the proportion with no disability (12.9%) (6) is much lower than the number provided for the alteplase trial (39% with alteplase vs. 26% without treatment) (5), which is because EVT is provided to the most severe strokes. EVT is often provided with alteplase, depending on a patient's eligibility for each treatment. Unfortunately, the availability of EVT is limited to larger centers due to the requirement for specific tools and trained staff available at Comprehensive Stroke Centres (CSC); in Nova Scotia, it is only available at one center. Patients eligible for EVT but arriving at a PSC need to be urgently transported to the CSC for EVT treatment.

In stroke, minutes matter, as the brain begins to undergo rapid deterioration shortly after the onset of symptoms (11), which makes the efficiency of receiving treatment with both thrombolysis treatment (12) and EVT treatment highly time-sensitive (13). Hence, timely access to EVT is crucial. PSCs must react quickly to ensure EVT-eligible stroke patients are transferred to the CSC as efficiently as possible. Eligibility for EVT is based on the imaging of the patient (8,14). The plain CT brain images show the extent of the ischemic core, as only patients with a small core are eligible, which indicates that there is a brain to save. The CT Angiogram (CTA) needs to confirm that the clot is in a large vessel accessible by the EVT procedure. Finally, the collateral circulation should also be assessed, as good collaterals keep the brain alive during transfer and during the EVT procedure (15). This is normally assessed using a multiphase CTA (mCTA) or CT perfusion (CTP). Despite our knowledge about selecting patients for EVT based on imaging, there is great uncertainty around how to best select patients for transfer from a PSC to a CSC. Research from Ontario indicated that 34% of patients with LVO who were transferred for EVT ultimately received the treatment. In other words, there is a great waste of resources, with 66% of individuals transferred for EVT were deemed ineligible for treatment upon arrival (16). Similar data from the US shows that only 27% of transferred patients received EVT (17). In Nova Scotia, only 44% received EVT when transferred from PSC between the dates of 2018 and 2021. Therefore 50-70% of severe stroke patients transferred from a PSC to a CSC for EVT treatment will not receive treatment; this is often called futile transfers. These futile transfers are creating a significant burden on the health systems as they are experiencing high levels of occupancy, severe health human resource shortages, and seemingly greater population morbidity, which is resulting in greater stress on the pre-hospital Emergency Medical Services (EMS) system, and delays in medical transfer between hospitals. Therefore, optimizing EVT response will free up scarce resources that are badly needed across the health system.

There are two opposing forces in this optimization problem. Over selecting patients for transfer to receive EVT leads to a greater number of patients that will receive the treatment; however, it also leads to a larger number of patients that turn out to be ineligible for treatment upon arrival. This essentially uses the philosophy to "cast a wide net"; however, over selection comes at a significant cost to the healthcare system due to the resources required for the urgent transport of a large proportion of severe stroke patients from remote hospitals to an EVT center who will not receive treatment. On the other hand, under selection or being more discriminant in selection results in missed cases and an overall lower number of patients from remote hospitals that will receive EVT, but the overall cost of transfer is lower since fewer patients are transferred. Additionally, time remains the largest factor for eligibility for EVT (12,15). However, several trials have shown that a highly select group of patients that arrive late (up to 24 hours after onset) still benefit from EVT (18,19). Therefore, there needs to be better processes developed to reduce the time from arrival at the peripheral site to departure for transfer to CSC, called door-in-door-out (DIDO) times (20,21). This research looks at the application of Data Envelopment Analysis to determine the efficiency of PSCs in their selection and transfer of ischemic stroke patients for EVT.

This thesis includes two studies that were conducted addressing application of DEA to emergency departments (EDs) and management of emergency conditions. This first study (27) is a narrative review that focuses on applying DEA in EDs and managing emergency conditions such as acute ischemic stroke and acute myocardial infarction (AMI). The second study applied DEA to optimize transfer times and futile transfers of ischemic stroke patients receiving EVT in PSC in Nova Scotia. Chapter 2 and Chapter 3 contain the manuscript for study 1 (27) and study 2, respectively. Each study manuscript includes sections and subsections, discussion that notes study limitations, as well as key findings. Chapter 4 includes a discussion that relates individual studies, interpretation of DEA results for healthcare administrators, limitations, and opportunities for future studies. Finally, Chapter 5 highlights the key conclusions drawn from the two studies and states the overall contributions of the works.

CHAPTER 2 Study 1- The Application of Data Envelopment Analysis to Emergency Departments and Management of Emergency Conditions: A Narrative Review (27)

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Journal: Healthcare. Multidisciplinary Digital Publishing Institute (MDPI). Volume 11, Issue 18, Pages 2540-2567.

Edited by: Andrea Tittarelli, Cancer Registry Division National Institute for the Study and Treatment of Tumors Via Venezian 1, 20133 Milan, Italy.

Publication Status: Published on 14 September 2023.

Student Contributions: Methodology, M.M.; Conceptualization, M.M.; Investigation, M.M.; Resources, M.M., Writing—Original Draft Preparation, M.M..; Visualization, M.M.

2.1 Abstract

Background: The healthcare industry is one application for data envelopment analysis (DEA) that can have significant benefits for standardizing health service delivery. This narrative review delves into the application of DEA within EDs and its effectiveness in managing critical emergency conditions, such as acute ischemic stroke and AMI. This includes benchmarking the proportion of patients that receive treatment for these emergency conditions.

Narrative Review: Most frequent primary areas of study motivating work in DEA, EDs and management of emergency conditions including acute management of stroke can be sorted into five distinct clusters in this study: (1) using basic DEA models for efficiency analysis in EDs, i.e., applying variable return to scale (VRS), or constant return to scale (CRS) to ED operations; (2) combining advanced and basic DEA approaches in EDs, i.e., applying super-efficiency with basic DEA or advanced DEA approaches such as additive model (ADD) and slack based measurement (SBM) to clarify the dynamic aspects of ED efficiency throughout the duration of a first-aid program for AMI or heart attack; (3) applying DEA time series models in EDs like the early use of percutaneous coronary intervention (PCI) in AMI treatment, and endovascular thrombectomy (EVT) in acute ischemic stroke treatment., i.e., using window analysis and Malmquist productivity index (MPI) to benchmark the performance of EDs over time; (4) integrating other approaches with DEA in EDs, i.e., combining simulations, machine learning (ML), multi criteria decision analysis (MCDM) by DEA to reduce the patients waiting times, and futile transfers; and (5) applying various DEA models for the management of acute ischemic stroke., i.e., applying DEA to increase the number of qualified acute ischemic stroke patients who receive EVT and other medical ischemic stroke treatment in the form of thrombolysis (alteplase and now Tenecteplase).

Results: We assess the methodological setups of the papers, offering detailed explanations regarding the applied models, selected inputs, outputs, and all relevant methodologies.

Conclusion: In conclusion, we explore several ways to enhance DEA's status, transforming it from a mere technical application into a strong methodology applicable to healthcare managers and decision-makers.

Keywords: data envelopment analysis; emergency department operations; acute management of stroke; stroke patients; emergency transfer to a tertiary hospital; acute stroke treatment; acute myocardial infarction treatment; endovascular thrombectomy; percutaneous coronary intervention.

2.2 Introduction

Healthcare systems worldwide are under pressure to provide timely access to urgent conditions in the emergency departments (EDs) as wait times continue to increase (28,29), creating greater demands to enhance their efficiency. However, assessing the effectiveness of EDs is a complex task that should not be underestimated. ED serves as a primary entry point to hospitals and plays a crucial role in hospital management. Due to the constant and unscheduled arrival of patients, the ED often experiences high levels of overload, leading to long waiting times for patients. This significantly impacts patients suffering from conditions such as stroke and myocardial infarction, which require immediate treatment in the ED (30-31). Therefore, EDs must be evaluated for their efficiency.

The potential tools to evaluate the efficiency of EDs include Data Envelopment Analysis (DEA). The fundamental concept of DEA is to identify an optimal performance frontier comprising efficient decision-making units (DMUs) that cover all the ineffective DMUs. The efficiency value for each DMU can be determined by measuring its deviation or gap between a point and the frontier. Over the past decades, DEA has progressively been applied to EDs, proving its suitability in this area. DEA possesses various characteristics that make it an appealing instrument for evaluating the performance of ED. Its ability to proficiently oversee numerous resources in the ED and monitor health results throughout the process of change is a notable benefit. EDs are typically the primary entry point for hospital admission. Because of the accidental nature of patients attending, the department should provide initial care for various diseases and damage, some of them could cause a risk to life or be potentially life-threatening and need urgent care. EDs of most health centers conduct 24 hours a day 7 days a week, although supervising levels may differ to reflect patient volume.

Bridging the gap between evidence and practice concerning the EDs' efficiency analysis is essential. Further research is needed to tackle methodological challenges in implementing efficiency analysis for EDs by managing emergency conditions effectively and enhancing the availability of valuable evidence. This article aims to make an initial step to increase our perception of how the application of DEA is applied in EDs to assist decision-makers in increasing the number of eligible patients who receive advanced treatments for conditions such as acute ischemic stroke and acute myocardial infarction (AMI) including the urgent transfer of these patients to receive the treatment.

The deleterious effects of delayed treatment have been observed in other emergency conditions such as early thrombolysis and percutaneous coronary intervention (PCI) in AMI or heart attack (32). Myocardial infarction (MI) is the result of a partial or complete occlusion of blood flow to a segment of the heart muscle. AMI might not exhibit noticeable symptoms and go unnoticed, or it could be demonstrated as a catastrophic occurrence causing a sudden drop in cardiovascular function and unexpected fatality. The primary cause of most AMIs is underlying coronary artery disease, which stands as the top mortality factor around the world. In cases of coronary artery blockage, the heart muscle is deprived of oxygen. AMI has conventionally been categorized into ST elevation or non-ST elevation myocardial infarction (33,34). However, treatments are comparable between these two categories, and a comprehensive overview of the general management of AMI can be provided for clarity. Despite significant advancements in prognosis over the last decade, AMI remains a prominent cause of illness and death globally (35). This progress can be attributed to various noteworthy trends, including enhancements in risk assessment, broader adoption of an invasive approach, establishment of care systems that prioritize prompt revascularization through procedures like percutaneous coronary intervention (or fibrinolysis), developments in antiplatelet medications and anticoagulants, and increased utilization of secondary preventive measures such as statins. Extended periods of inadequate oxygen delivery to the heart muscle can result in the death and decay of myocardial cells. As the primary goal of thrombolysis is to swiftly reestablish blood circulation to the at-risk heart muscle to protect its cellular structure and operation, the factor of time becomes a critical limitation that hinders the beneficial outcomes of thrombolysis and PCI (36).

Finally, this narrative review aims to review the application of DEA as an important approach of MCDM to EDs and the management of emergency conditions. Initially, we review the correlation between the notion of 'efficiency' in DEA and 'convex efficiency' in MCDM through a basic model. Through some related references, we demonstrate that certain integrated methods such as machine learning and simulation suggested in the DEA field for addressing MCDM issues contradict fundamental normative principles that are widely acknowledged.

2.3 Techniques and Views

This section comprises five subsections that encompass diverse integrated DEA approaches, all aimed at illustrating the role of these approaches in relation to EDs:

2.3.1 Applying Basic DEA Models for Efficiency Analysis of EDs

DEA models, CCR and BCC, differ in their treatment of scale returns, with CCR assuming constant returns and BCC allowing for variable returns. Ongoing modifications to these models reflect a persistent debate on their dominance. The choice between the two models depends on the dataset characteristics. A study by Banker et al. suggests CCR performs better with smaller sample sizes (up to 50 DMUs), while BCC is more effective with larger samples (at least 100 DMUs). Input-oriented DEA models minimize inputs for a given output, while output-oriented models maximize outputs with constant inputs; hybrid models aim to optimize both inputs and outputs for efficiency (37)**.**

Figure 1 summarizes basic DEA models including input oriented CCR dual model (a) Visual representation of technical efficiency and its breakdown from various sources in a graphical format considering pure technical efficiency (PTE), technical efficiency (TE), and scale efficiency (SE), and (b) Frontier lines considering input and output-oriented visualization.

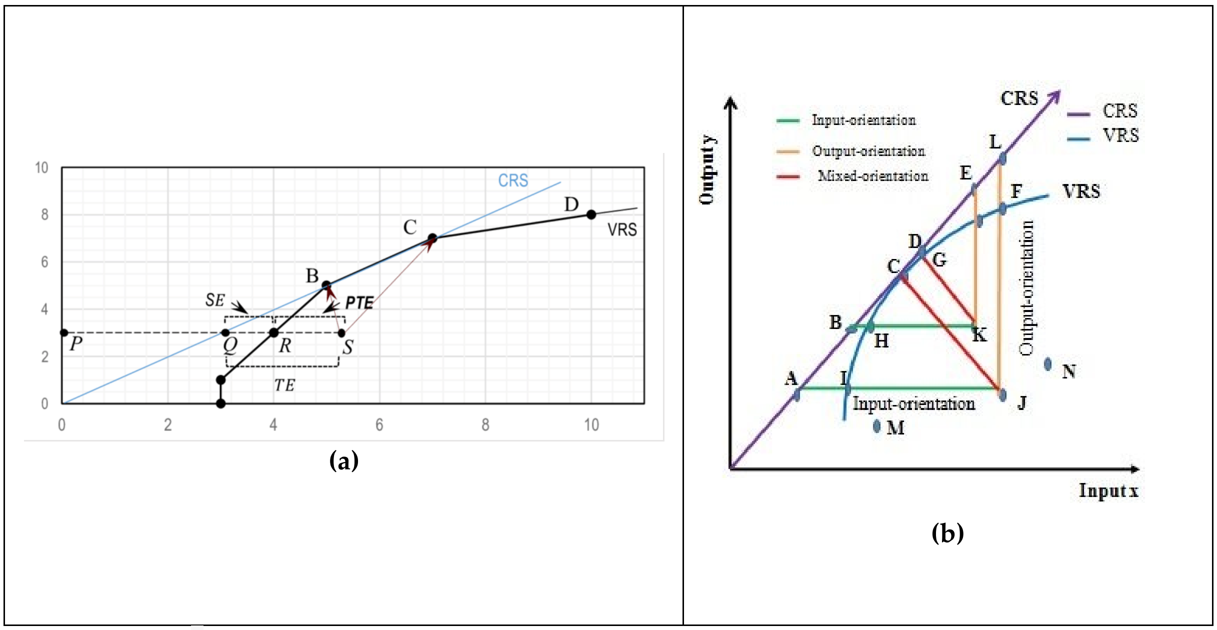

Figure 1: a) Visual Representation of Technical Efficiency and Its Breakdown from Various Sources in a Graphical Format Including PTE, TE, and Scale SE, b) Frontier Lines Considering Input and Output Oriented and Mixed Oriented Visualization.

Table 1. summarizes the characteristics of input and output oriented for basic models.

Table 1: Characteristics of Input and Output Oriented for Basic DEA Models.

Characteristics	CCR input-oriented	CCR output-oriented	BCC input-oriented	BCC output-oriented
Return to scale (RTS)	CRS	CRS	VRS	VRS
Sign of the inputs	Semi-positive	Semi-positive	Semi-positive	Free
Sign of the outputs	Free	Free	Free	Semi-positive
Type of efficiency	Overall Technical	Overall Technical	Pure Technical	Pure Technical
Surface of envelopment	Piecewise linear	Piecewise linear	Piecewise linear	Piecewise linear
Metric of envelopment	Radial ([0,1])	Radial ([1,∞])	Radial ([0,1])	Radial ([1,∞])

The initial study was conducted by Hao et al. (38) in 1978. They suggested the CRS approach assisted by multiple regression analysis to assess the efficiency of acute care veteran's affairs hospitals including the hospital's ED. The study excluded hospitals that were smaller in scale, housing fewer than 100 beds and those that had not been operating for 12 months. Various forms of analysis were applied to evaluate the efficiency of these hospitals. Two types of analysis used in this study were assessment of productivity and input-oriented, focusing on key outputs of medical procedures, patient releases, and visits to the emergency room and outpatient services. Therefore, the techniques employed in this study rely on quantitative input, including the sum of staff, the sum of medical beds within the hospital facility, and the corresponding sum of full-time nurses and physicians. It's important to note that none of these inputs or outputs were measured in monetary units. Consequently, they were not susceptible to fluctuations in the currency's worth or changes in the dollar's cost across different locations in the country where the hospitals were located. Multiple regression analysis was employed in combination with DEA to determine the relative efficiencies. The outcomes of the study showed that approximately half of all hospitals could improve their efficiency. Additionally, the study found that the dimensions of the hospital, inpatient surgical procedure, outpatient surgical procedure, and combined emergency room and outpatient visits were factors that had a significant impact on good efficiency values. Finally, they provided valuable insights into the efficiency of acute care veteran's affairs hospitals and identified areas where improvements could be made. This research methodology allowed for a comprehensive evaluation of the hospitals and provided a basis for further analysis and potential enhancements in healthcare.

Many research papers have explored basic DEA models for public hospitals and acute care centers (39-43). However, in this narrative review, our focus is only on the following articles assisted by basic DEA models for EDs:

Akkan et al. (44) applied VRS and CRS models for the efficiency evaluation of the EDs for seven general hospitals in Istanbul's Beyoglu state hospitals. Four essential and interconnected variables were determined for assessing the efficiency of the EDs. These variables were carefully selected based on the critical and relevant data accessible. The first two variables were considered as inputs: the total bed capacity within the ED and its corresponding level. The other two variables were regarded as outputs: the sum of patients seeking emergency medical attention attended to in the ED and the sum of patients referred from the ED. Out of these variables, the classification or status of the EDs held significant importance as it influenced the selection of the appropriate DEA model and set the suggested model apart from many other models. DEA, assisted by statistical methods, was applied to make it easier for hospital managers to extract hidden rules. The small number of hospitals in this study was one of the weaknesses.

EDs play a vital role in Jordanian hospitals. Waiting times for ED patients were a critical and common problem. Therefore, Al-Refaie et al. (45) proposed a DEA-based approach to decrease the average waiting time for patients in the ED, improve the nurses' efficiency, and increase the quantity of waiting patients. The inputs in this scenario included the sum of nurses and the typical length of stay (LOS) in the ED, where smaller values were favored. On the other hand, the outputs consist of the average percentage of nurses and the number of patients served, where larger values were preferred. A proposal for a cellular service system was made, and it was implemented to schedule ten nurse appointments. To assess the performance measures for each design, the simulation was executed with ten replicates, each spanning one month (672 hours). The optimal outcome was established by applying aggressive CRS formulation. The results presented that the optimal approach relies on distribution of workloads among different individuals or teams, which reduced patients' mean waiting time from 195 to 183 minutes, increased the number of patients attended from 8853 to 8934 and improved the nurses' operation from 52% to 62%. Ultimately, the adaptability of nurses within cellular service systems provides valuable support to hospital administrators aiming to improve the efficiency of the ED.

Chu et al. (46) applied the VRS assisted by multi objective linear programming

(MOLP) for allocation of healthcare resources in hospitals during times of public health emergencies in China. Initially, the DEA was implemented to guarantee that the ED can constantly indicate state-of-the-art knowledge through all operational periods. Each hospital was considered a DMU that utilized various inputs to create desired outputs. The suggested inputs for a DMU consist of four main factors including the number of doctors and nurses, ICU beds, personal protective equipment (PPE) requirement, and fixed assets. The outputs comprise the sum of patients who have been admitted, the sum of patients who have been released, and the number of fatalities or the number of deceased individuals. The sum of patients who have been admitted and the sum of patients who have been released were considered desirable outputs, representing successful medical care. Conversely, the number of fatalities was classified as an undesirable output, reflecting the negative outcome of patient care. According to the suggested model, two models for assessing efficiency were organized to determine the effectiveness levels of EDs before and after resource allocation. The findings indicated that all the EDs achieved efficiency following the allocation of medical resources, and therefore an innovative resource allocation possibility was determined. For the MOLP, the first objective was to optimize the output, while the other objective was to link the allocated resource to the operation size of each ED.

Omrane et al. (47) proposed VRS input oriented for ambulatory care departments. Four EDs demonstrated a relatively effective performance throughout the three years. Using a DEA model, they evaluated relative efficiencies by considering the available personnel (physicians, nurses, and managerial personnel) as inputs and the number of outpatients who have received treatment as the output. Consequently, they computed efficiency scores for each ambulatory care unit from 2014 to 2016, allowing them to pinpoint the inefficient units in terms of resource utilization and outpatient treatment. The findings from this research were regarded as valuable for managers in assessing the potential reduction of human resources in outpatient units without cooperating with their ability to fulfill tasks and avoid wasting limited resources. They identified potential adjustments based on their relative efficiency to aid decision-makers in hospital management and enable the optimal allocation of human resources. These adjustments aim to help address inefficiencies in certain EDs and implement appropriate countermeasures.

Ketabi et al. (48) suggested CRS input-oriented to evaluate and compare 24 EDs in Iran. The selected factors were categorized into two groups: the first subset included input factors such as the number of active beds, physicians, nurses, and medical equipment. The second subset consisted of output factors, which encompass the number of discharges, the proportion of cases where revival or recovery occurs, typical duration of waiting, and the level of contentment or satisfaction expressed by patients. The model can be employed to identify the reasons for inefficiency and determine strategies for enhancing performance. Based on the suggested data, 37% of EDs were inefficient. The primary causes were the surplus of medical devices and staff members. So, DEA offered a collection of anticipated input/output quantities or levels that could make EDs comparatively effective.

During the COVID-19 pandemic, physicians and EDs faced a significant challenge. The increasing entry of patients seeking treatment in EDs led to overcrowding, subsequently impacting the quality of services provided. Consequently, the management and operation of EDs became even more pressing during the pandemic. Addressing this issue, Taghipour et al. (49) initially applied four basic input and output-oriented DEA to assess the efficiency of EDs located in the provinces situated at the center of Iran. The main factors were door-to-doctor time, number of admitted patients, employee absence rate, percentage of complaints handled, number of patients waiting in a queue, number of test kits, time required for receiving the test results, and finally the proportion of isolation rooms about the total area of the ED that are theoretically anticipated to have an impact on the performance of EDs during the pandemic. For this research, indicators with favorable outcomes with lower levels/ranks, examples include the duration of hospitalization and the time spent in boarding, were designated as inputs. Conversely, indicators with desirable outcomes with higher levels/ranks, including the sum of patients who have been admitted and the sum of test kits, were assigned as outputs. Subsequently, they conducted a sensitivity analysis to identify the key factors impacting the efficiency of this department. Their findings highlighted the significant factors influencing efficiency which were the high number of admitted patients, ward congestion, and the extended time taken to report COVID-19 test results.

2.3.2 Combining Advanced and Basic DEA Approaches in ED Applications

An ongoing debate in DEA turns around the choice between input-oriented and output-oriented approaches. Charnes et al. (50) proposed a third model, the Additive model (ADD), which integrated both input and output oriented. The input and output slacks are determined in ADD and optimized for the DMU to maximize their value. Thus, ADD minimizes the inputs while concurrently maximizing the outputs. Furthermore, inefficiencies extracted from slacks are provided in the analysis score. However, the initial ADD model should provide scalar efficiency evaluation. Table 2 summarizes the characteristics of the ADD.

Table 2: Characteristics of the Additive Model.

Characteristics	Additive Model
RTS	CRS&VRS
Sign of the inputs	Free
Sign of the outputs	Free
Type of efficiency	Mix of both
Surface of envelopment	Piecewise linear
Metric of envelopment	[0,1]

Tone's (51) development of the slacks-based measure (SBM) suggested a new idea in this issue. The SBM continuously reduces within each slack, with its measurement ranging between zero and one. SBM sets aside the notion of proportional adjustments in both inputs and outputs and directly addresses the concept of slacks. This method has three variations, specifically input-oriented, output-oriented, and non-oriented approaches. The SBM models are created to fulfill the two requirements of Units' invariance **(**The measurement remains unchanged regardless of the units used for the data) and Monotonicity (The measurement should consistently decrease with each slack in both input and output).

Table 3 summarizes the characteristics of SBM model.

Table 3: Characteristics of the Slack Based Measurement Model.

Characteristics	SBM model
RTS	CRS&VRS
Sign of the inputs	Semi-positive
Sign of the outputs	Free
Type of efficiency	Mix of both
Surface of envelopment	Piecewise linear
Metric of envelopment	[0,1]

Super-efficiency involves systematically ranking units with efficiency scores of one.

The model uses standard DEA models, assuming the assessed unit is not in the reference set. It estimates the increase in a unit's inputs while maintaining efficiency relative to others. The super-efficiency score serves as an indicator of stability, assessing variations in input data without compromising the unit's efficient status. This approach provides a systematic ranking method based on performance relative to a set of benchmarks (26,52). Du et al. (53) applied advanced DEA to compute the efficiency of hospitals. They employed an integrated SBM super-efficiency model to assess hospitals providing comprehensive acute care services. The model considered the common selection of variables for inputs and outputs and considered the health outcome quality measure represented by the survival rate among the suggested outputs. In this study, every hospital within the sample was considered a DMU, which employed inputs encompassing both the physical and monetary aspects to generate outputs, representing healthcare services and the subsequent health conditions. As a result, the proposed model evaluated both the quantity and quality of the outputs. By using this DEA model, inefficiencies in the DMUs were identified and addressed without compromising the quality of care provided.

Dexter et al. (54) performed research where they employed data resampling methods to explore different statistical choices for super-efficient DEA. This was done either for comparative purposes or as a reference for administrators overseeing DMUs in rural, teaching, and state hospitals. The output in this context was the number of hospital discharges, which included the specified procedures. On the other hand, the inputs comprised the staffed acute and intensive care beds available at the hospital, as well as the surgeons who carried out a minimum of three cases for any of the eight procedures, such as cardiac and neurological surgery, at the hospital. Their primary focus was on identifying the disparities in the outputs, considering slacks adjusted to account for favorable inclination or tendency to determine areas where improvements could be made. Through numerical experiments, they observed that the estimations of the output differences did not exhibit approaching or tending towards uniformity as the values increase indefinitely, a characteristic that is commonly anticipated in standard numerical assumptions. They found that larger sample sizes did not consistently lead to more precise predictions of the output gaps. The gaps obtained from the baseline DEA correlated with the jackknife mode and the resampling mode, with or without additional data from any specific population subset. In most cases, the baseline DEA gaps were also equal to the median. These findings highlighted the importance of considering DEA results with sensitivity analysis, where one benchmark DMU was ignored at a time. The sensitivity analysis proved to enhance the effectiveness of decision support provided by DEA by identifying the capability of a DMU to improve one or multiple outputs.

In the following, we selected papers that specifically examined advanced DEA in the context of EDs:

Fiallos et al. (55) suggested an SBM-VRS model to evaluate the performance of ED. Within the ED, there was a lack of motivation to adopt a methodology that examined the correlation between the effects on outputs and the increases in inputs, this led them to focus on models that allowed for VRS. In the model, quantity measures were utilized as inputs, while quality measures served as outputs. This study focused on three inputs: the mean duration of individual appointments, the mean count of laboratory tests, and the mean count of radiology orders for each appointment. The only output considered was the level of non-return individual appointments within 72 hours. They examined the significance of employing a sophisticated approach that recognizes the diversity of patients an ED physician encounters and the crucial role they serve as advisors for instructing other physicians. So, patients were gathered along with their representative medical problem, and ED physicians evaluated each group independently. Performance differences were evident among physicians in each complaint group and set. A secondary categorization separated patients according to whether they were attended by a trainee in addition to the primary joining physician. Practically every ED physician exhibited improved performance when they were not assisted by beginners.

Agovino et al. applied SBM for EDs in Italy (56). The main objective of this study was to clarify changing aspects of the efficiency of the ED during an emergency medical assistance program. So, they applied an analysis of the city of Sorrento conducted in two stages. An efficiency analysis was conducted using two inputs and two outputs. The outputs were categorized as favorable results, representing the sum of individuals seeking medical attention or treatment who experienced improved medical conditions or ailments related to a person's well-being after medical care provided in the ED, and unfavorable outputs, which represented the sum of individuals who experienced worsening health conditions after medical treatment. The main goal was to assess the effectiveness of first aid in enhancing patients' health conditions. Both output variables were established based on the triage code, which serves as a reliable indicator or factor that can help determine a patient's degree of immediacy and, consequently, the ED's ability to provide appropriate treatment. Additionally, the check-out code was also considered in the analysis. They incorporated two time-based variables as inputs for their analysis: access time (AT) and healthcare time (HT). Both factors were computed as the daily wait time's median. The AT was used to obtain the period starting from the time a patient entered the phase of triage or the triage level till a physician conducted the first examination. This quantity represented the duration of time spent waiting to receive first aid and critical information provided for patient healthcare support. A greater value for AT indicated poorer performance of the ED. On the other hand, HT quantity represented the duration of health treatment from the patient's initial health examination until their discharge. First, they used SBM to explore the changing efficiency patterns of the Sorrento ED. Secondly, they utilized a filter to verify if variations in ED efficiency were implemented through the gradient of the supply curve for first aid services. In conclusion, a potential solution might involve adopting a flexible management approach for medical and nursing staff. This would involve incorporating daily and seasonal planning that considers fluctuations in work intensity. Such planning would empower Sorrento's ED to function more efficiently, even during periods of reduced demand.

Since health transformation programs (HTP) and EDs are the most critical aspects of the health sector, Bozdemir et al. (57) applied super-efficiency to VRS and CRS models to remove multiple efficient DMUs for EDs. To assess the efficiency of health activities, three inputs and three outputs were considered. The inputs comprised the gross domestic product (GDP) share of current expenditure on health, the number of graduates from medical faculties per 100,000 population, and the rate of deaths per 1000 live births (infant mortality). On the other hand, the outputs consisted of the number of beds per 1000 population, life expectancy (representing the regular life expectancy at birth, assuming mortality rates remain constant across different age groups), and the percentage of the total population aged 65 and over. The main objective was to evaluate the achievement, effectiveness, and endurance or long-term viability of HTP; in this situation, they considered two separate case studies. First, Turkey’s efficiency was assessed during 2003–2016 in the health sector and based on the first scenario, Turkey was inefficient during 2003–2012. The main reason for their being inefficient was investment. The second case study compared Turkey with nine other countries based on GDP, and it was observed to be efficient except in 2007. Finally, Turkey ranked fifth among the ten countries regarding the average efficiency score.

Ngee-Wen et al. (58) utilized a retrospective observational approach, analyzing data on support staff, doctors, discharges, arrival times to consultants, and LOS. For this study, two inputs were selected: full-time equivalent staff (representing the total number of support staff, including nurses and medical assistants) and full-time equivalent medical (comprising the total number of doctors, including medical officers, specialists, and consultants). Moreover, one output was considered, which was the number of discharges (representing the total number of discharges in the ED for a given year). These inputs and outputs were selected based on their extensive use as variables in DEA healthcare research. Two additional outputs were included: arrival to the consultant (representing the total number of patients with an arrival time to the consultant less than 90 minutes) and LOS (representing the total number of patients with LOS less than 120 minutes). The inclusion of these outputs was determined by lean key performance indicators employed to track the results of lean healthcare implementation. Efficiency scores were then computed for 20 public EDs in Malaysia using SBM. These scores were then compared before and after the implementation of lean practices. In evaluating the outcomes of Lean healthcare, several key performance metrics were typically employed. However, the current deficiency lies in the absence of adequate tools to assess efficiency in this context. After the introduction of lean implementation, 13 out of the 20 EDs showed progress in reducing the LOS and the time it takes for a patient to arrive and see a consultant or specialist. On the other hand, it is worth noting that out of these 13 public EDs, only 9 of them experienced an improvement in their efficiency score. Lean healthcare has been proven to positively impact the efficiency of specific EDs. The SBM model provided comparative analysis capabilities and valuable information for slack removal, which can complement the principles of continuous improvement in the context of lean practices.

Azadeh et al. (59) assessed three categories of inaccuracies, which involved insecure transport, multiple or recurrent needle punctures into a vein, and errors in the process of collecting samples. The suggested inaccuracies were incorporated into a simulation model. A total of seventy suitable settings, validated by specialists in ED, were outlined to evaluate different options. These settings were then analyzed and assessed using stochastic DEA (SDEA) to identify the optimal solutions. In this study, the inputs consisted of cost, number of nurses, and number of physicians, while the outputs included waiting line, the length of time a patient spends or stays in a particular situation or medical setting, and the number of three distinct mistakes that were made or committed. The findings showed that adding additional nurses and physicians or incorporating a larger number of nurses and physicians in the ED would lead to a reduction in human errors, patient duration, and queue length.

2.3.3 Applying DEA Time Series Models to EDs

MPI and window analysis are the two most common DEA time series approaches for measuring productivity and efficiency respectively. Various methods can be employed in productivity evaluations to calculate productivity changes, including the Fisher, Tornqvist, and Malmquist indexes. Among these, the Malmquist total factor productivity (TFP) index, introduced by Malmquist (60), is the most used analytical tool for assessing productivity changes.

The MPI offers three key advantages over the Fischer and Tornqvist indexes. Firstly, there is no need for information on optimizing earnings or minimizing expenses. Secondly, there is no need for data on input and output prices. Lastly, when applied to panel data, the MPI enables the separation of productivity changes into two separate elements: technical efficiency (also known as catching up) and technical change (which refers to alterations in best practices).

The DEA window analysis operates based on the concept of moving averages, as initially proposed by Charnes et al. (61), and it proves valuable in identifying efficiency changes observed in a unit over a period. In this approach, each unit is considered a separate entity in separate periods. Consequently, the efficiency of a specific component in a particular period is evaluated not only with its efficiency during different timeframes or in alternate periods but also with the efficiency of other components. By incorporating additional data points into the analysis, this method becomes particularly useful for situations with small sample sizes.

Trakakis et al. (62) conducted a study using the input oriented MPI approach, considering both VRS and CRS, to examine the total productivity of 155 rural primary care hospitals in Greece. Twelve outputs were identified, which included the total number of nursing activities, small-scale surgical procedures or minor surgeries, dental treatments, cases of long-term or persistent medical conditions, emergencies, urgent events, transcriptions, bio pathological and laboratory exams, vaccinations, and vaccinations for kids and teenagers. Inputs consisted of the total number of managerial employees, doctors, nursing staff, and non-medical staff. The research aimed to assess the productivity of each of the 155 DMUs in Greece and analyze how it changed during the period from 2016 to

2018. Additionally, the study evaluated the overall productivity change of all 155 DMUs over time. The mean value analysis revealed there was a decline of 0.9% in overall productivity between 2016 and 2017. and a further reduction of 5.2% from 2017 to 2018, resulting in a total reduction of 3.1% in the productivity of all 155 DMUs. The findings from this model can provide valuable insights into the performance of each rural health clinic. In a related study, Bağcı et al. (63) proposed a time series DEA-based MPI using CRS and VRS models from 2011 to 2016 in rural hospitals in Turkey. As input variables, the study considered the total number of beds, specialists, residents, general practitioners, nurses, and midwives, other medical personnel wages and benefits, other service expenditures, raw materials and supply costs, and overall administrative costs. As for the outputs, the study applied the number of inpatients, outpatient, and surgical operations for three suggested groups, and working capital turnover. The research revealed that the proportion of efficient rural hospitals decreased from 2011 to 2016, indicating that the organizational and financial management of rural hospital supervisors may have contributed to lower productivity.

Zhou et al. (64) applied the same MPI time series DEA, assisted by the Tobit statistic model, to analyze factors influencing productivity in 28 urban and rural areas. The input variables in this study consisted of the sum of institutions, the sum of beds, and the sum of health technicians. Alternatively, the output involved the sum of outpatients and emergency visits, as well as the quantity of discharged patients. They found that the concentration or distribution of the population and the ratio of dependents (non-working population) to the working-age population were the primary aspects influencing the technical efficiency of rural areas. As a suggestion to improve productivity, the authors recommended improving medical technology in rural clinics through technology restoration.

Jia et al. (65) performed a time series DEA window analysis, assisted by CRS and VRS, to assess the operational efficiencies of EDs in five hospitals over seven years. The data pool used in the study was provided by health authorities. Consequently, they considered two inputs of the real count of beds and staff members at the termination of the period. Three outputs were considered the sum of out-patients and EDs, the sum of patients who have been discharged, and the mean duration of hospital stay at the termination of the period. The results revealed that the sample EDs exhibited an overall increasing trend in their operational efficiencies, comprising TE, PTE, and SE over seven years. However, there was a brief decline shortly after the hospital's organization, with PTE showing more improvement in comparison to SE. Particularly, the creation of separated hospitals did not have a lasting adverse impact on efficiencies in hospital operations. The final findings suggested the impact of increasing SE through enhanced organizational management and highlighted the benefits of adopting different branch organizations, merging, and restructuring. This study provided valuable insights into the real-world operation of DEA window analysis for measuring basic operational efficiencies of EDs.

Mohd Hassan et al. (66) proposed an evaluation of cross-sectional efficiency for 76 EDs. For this analysis, the cost of ambulance services was considered as the input, and the output variables included the extent of geographical coverage or distance span (kilometers), the sum of transferred patients, and utilization hours. The evaluation of TE assuming CRS is known as overall technical efficiency (OTE). When VRS is considered, OTE can be divided into two separate components: PTE or managerial efficiency, and SE. PTE and SE are distinct from each other and cannot be merged or combined. In this study, further assessments were applied to examine the OTE, PTE, SE, and RTS for different health facilities and geographical regions. For these analyses, the Mann-Whitney U-test and chi-square test were applied. The primary reason for the disparity in OTE among hospitals and EDs was their operating size rather than the PTE.

2.3.4 Integrating Simulations, ML, and MCDM with DEA for the Management of Emergency Conditions in EDs

DEA can be integrated by various commonly used techniques, such as MCDM, artificial neural network (ANN), logistic regression, and discrete event simulation (DES). MCDM originated from operations research (OR) and includes various approaches. MCDM is a method for ranking a finite number of alternatives assisted by multiple criteria. It evaluates and selects alternatives that fit the objectives and requirements (67).

DEA benefits from the incorporation of ML algorithms, such as ANN and logistic regression. ANN draws its inspiration from the brain's primitive sensory treatment models, which can be simulated using a network of model neurons in a computer. By implementing algorithms that mimic real neuron processes, the network can "learn" and effectively solve various problems. The ANN collects input from different units and produces an output of one if the total input exceeds a specified threshold, otherwise, the output is zero. The output transitions from 0 to 1 when the total weighted sum of inputs reaches the threshold (68). On the other hand, logistic regression is a widely utilized ML algorithm, specifically falling under the supervised learning technique. It is employed for predicting categorical dependent variables based on a given set of independent variables. Logistic regression is well-suited for forecasting the outcome of a categorical dependent variable (69). Simulation studies have long been applied in healthcare to address delays and challenges associated with the healthcare system. Researchers have explored numerous alternatives, considering factors such as processes within the organization, and level of staffing applying simulation models to enhance the performance of EDs and decrease patient waiting times. DES suggested by Günal et al. (70) is a prominent tool employed for analyzing and optimizing healthcare systems. It is frequently integrated with DEA in various research articles. DES evaluates the functioning of a system as a series of distinct events occurring chronologically. Every occurrence takes place at a designated moment in time and results in a state of systematic modification. When there are no changes between consecutive events, the simulation time can instantly advance to the time of the next event, known as the next-event time progression.

Several studies have proposed integrating DEA with ANN or logistic regression for acute care hospitals (71-74). Additionally, many research papers have suggested DEA with DES for acute care centers (75-79). However, in this narrative review, our primary focus is only on the evaluation of the following articles that considered integrating the suggested approaches with DEA models in EDs:

Despite the critical role of ED performance measurement, commonly applied metrics need to be normalized. The objective of Kang et al. (80) research paper was to suggest an efficiency indicator that supports evaluating EDs in connection with TE and SE. They explored critical exogenic components concerning the TE of EDs. According to the provided information, the suggested research was an initial study that analyses the scale and technological efficiencies of EDs. This study applied input-oriented DEA models that considered six inputs and outputs and created an efficiency ranking for specific EDs. The inputs for the evaluation consist of three variables: the number of ED beds, clinical staffing working hours, and non-clinical staffing working hours in the ED. On the other hand, the outputs include three measures: the daily sum of patient visits, the average LOS, and the rate of leaving without being treated. The DEA analysis suggested that a considerable number of EDs might not require adjusting their operations' range to increase efficiency. Alternatively, they might have to re-engineer specific procedures to apply suggested inputs effectively. The logistic regression supported those different operational segments within the ED, the LOS, and the percentage of patients arriving by ambulance related to the TE of EDs. Using these models as strong tools used for comparing and evaluating performance, the results can serve as a foundation for improving EDs' performance by focusing on critical hospital resources.

EDs need to adopt effective systems that reduce expenses while ensuring satisfactory levels of care. The main objective of Weng et al. (81) was to create and implement a combined approach using DES and DEA. In this research, the study considered different types of ED resources as inputs, which included the number of physicians, nurses, and beds. The output aimed to evaluate how modifications in these input levels influenced the efficiency of ED operations, leading to the identification of the most efficient resource allocations. This approach aims to assess possible bottlenecks, optimize throughput, and find solutions to decrease patient waiting times in the ED while enhancing patient satisfaction. The same integrated approach was applied by Aminuddin et al. (82) to determine the highest potential demand that the ED can handle using its existing resources. DES was employed to examine the waiting time patterns of ED visits and forecast the peak demand. DES-DEA was applied to identify the optimal decision for the number of resources (doctors and nurses) necessary to sustain their efficient services. The inputs in this approach include the sum of physicians, nurses, and the overall mean waiting time for patients. On the other hand, the outputs consist of the average use of doctors, the average use of nurses, and the number of patients served. The primary goal was to minimize the overall mean waiting time while applying the lowest possible resources, considering the provided rate of resource utilization on average and the sum of patients attended. The most effective improvement was identified through the implementation of the BCC input-oriented method and super-efficiency method. The proposed improvement can serve as an initial benchmark for hospital administration to make informed decisions while addressing the problem of overcrowding.

Due to demographic change and aging people's growth, timely access to health services has become increasingly difficult. These make many difficulties for patients and medical setups. Acute hospitals are experiencing an unprecedented level of overcrowding because there is a shortage of available acute beds. Consequently, patients in need of treatment experience prolonged waiting periods as healthcare providers focus on whether to admit them, transfer them to another facility, or discharge them to go home. These extended waiting periods frequently lead to patients entering various locations within the hospital. So, it causes a risk to patient safety and reduces the level of service provided whereas raising the expenses associated with medical care.

Keshtkar et al. (83) proposed an integrated simulation methodology that allowed hospital managers to consider the patient waiting challenge. Merging dynamics and DES assisted the manager in facilitating the difficult patient movement at both larger, overall levels and smaller, specific stages. Design of experiment (DOE) and DEA were incorporated into the simulation to efficiently evaluate the operational consequences of different management interventions. In CRS and VRS models, some DMUs are efficient with an efficiency score of one, and some DMUs with an efficiency score of lower than one are inefficient. Sometimes, several DMUs may get the efficiency score of one. Thus, to address this issue, the super-efficiency method was applied by ordering DMUs based on their efficiency levels. The DMU with the highest super-efficiency score is considered the best. The VRS output-oriented performed better than other models and was considered for ranking.

The gap between the number of doctors and nurses and the patient ratio creates a bottleneck in the available resources, leading to long waiting times for patients, particularly after office hours, and during weekends. To achieve the optimal resource allocation for the two shift groups, a combination of DES integrated by BCC input-oriented and super efficiency methods was proposed by Yusoff et al. (84). This approach generated multiple resource allocation options for doctors and nurses, amounting to 64 options available for weekdays and 729 options available for weekends. The DES model provided the values for the mean waiting time, the mean operation rate of physicians, the mean operation rate of nurses, and the number of patients who have been attended to or treated. In terms of preference, the sum of physicians, the sum of nurses, and the mean waiting duration were considered inputs, since values that are smaller in size were favored. Conversely, the mean usage or occupancy of physicians, the mean usage or occupancy of nurses, and the number of patients who have been attended to or treated were designated as outputs, since higher values were favored for these variables. The findings revealed that the optimal distribution of physicians and nurses during weekdays consists of a team of three physicians and three nurses for each work period. During weekends, the most effective group consists of four physicians and four nurses for each work period. These recommended arrangements have resulted in reduced average waiting times, improved utilization of medical staff, and an increased number of patients attending during weekdays and weekends. The same DES-DEA was proposed in recent studies (85-86). The main objective was to increase the efficiency of the hospital's EDs, aiming to minimize patient waiting times and optimize resource utilization. The outcomes underscored the significance of maintaining a well-balanced number of doctors within the ED to uphold an acceptable patient throughput time. Finally, Rabbani et al. (87) proposed DES-DEA in the last DES suggested article. This paper applied the clinical pathway as a crucial element for the integrated simulation of the ED due to the significant interactions of laboratories, radiology departments, and pharmacies. EDs deal with a range of patients, each having unique priorities. This leads to the necessity for distinct response variables, creating a multi-response optimization problem. To address these resource allocation challenges, a novel approach that combines DEA, DOE, multi-layer perceptron, ANN, and radial basis functions was introduced. Due to the expensive and limited nature of healthcare resources, the model incorporated budgetary and resource restrictions.

The healthcare sector is facing a notable and continuously expanding issue with human errors. Yazdanparast et al. (88) suggested both resource allocation and human error to optimize the use of resources in an ED. Six inputs were the number of triage nurses, physicians, nurses, beds, CPR units, and oxygen capsules. On the other hand, six outputs were the average wait time of patients, considering the weight or significance of each case, the average waiting time for patients during the triage process, the rate or occurrence of errors related to skills or competencies, the score or measure of redundancy or duplications, the average waiting time for beds or the typical duration patients wait to be assigned a bed, and fee. The algorithm consists of four main components: simulation, ANN, DOE, and fuzzy DEA (FDEA). The approach aimed to optimize multiple aspects, including human error, cost, wait time, patient safety, and productivity. The simulation helped establish the link between human resource utilization and human error. Furthermore, ANN was employed to predict response variables, while FDEA was applied to determine the optimal scenario.

Kang et al. (89) proposed a data-oriented framework to compare and establish efficient EDs, along with implementing their most effective methodologies. Initially, they employed DEA to recognize the frontiers of efficient operations in the EDs. Then the ED benchmarking alliance database from 2012 categorized 449 EDs into six groups and assessed the efficiency of each ED within those groups. The components considered as inputs in this context were the number of ED beds, clinical staffing working hours, and non-clinical staffing working hours within the ED. On the other hand, the outputs consist of the daily sum of patient visits, the average LOS, and the rate of patients leaving without being treated. After obtaining the efficiency rankings, logistic regression was employed to determine the specific attributes of EDs that influenced their classification as either efficient frontiers or inefficient units. The findings revealed that the efficiency of the EDs was significantly influenced by the proportion of admitted patients entering through the ED, the utilization of a mid-level provider intake model, the presence of a fast-track area, and the overall patient volume.

Labijak-Kowalska et al. (90) applied an extensive investigation into the resilience of efficiency results concerning various input and output weights. They achieved this by applying mathematical programming and the Monte Carlo simulation. They examined three inputs, namely, the mean duration of each patient's appointment, the mean sum of laboratory tests conducted during each patient's appointment and the mean sum of radiology requests made during each appointment. Additionally, they used an output, which was the level of non-return individual appointments during a time frame of 72 hours. They concentrated on a particular subset of patients who primarily presented expressions of discomfort in the abdominal region and constipation. However, during their analysis involving multiple scenarios, they also considered two additional groups with complaints connected to instances of fever, as well as injuries affecting either the lower or upper limbs, head, and wounds involving lacerations or punctures. Specifically, they employed the ADD for their analysis. They concentrated on evaluating physicians' performance in handling different groups of patients' complaints. The results that were obtained highlight how much physicians' performances relied on the specific weight vectors that were selected. Additionally, they provided a foundation for creating a plan to enhance the performance of physicians who are not meeting performance expectations or are performing below the desired standard, deciding on the main priorities for a practice-oriented model, and detecting the most challenging issues raised by patients.

DEA assisted by MCDM in EDs proposed in recent studies (91-92). Abdel-Basset (93) applied DEA integrated by MCDM to assess the efficiency of EDs in 20 hospitals. This assessment was based on two key criteria: the sum of patients who received treatment. and the impact on the standard of living experienced by a patient, which was evaluated by applying 11 different factors. In this research, 11 inputs that directly and indirectly impact the operations of the ED were taken into consideration. The suggested inputs have been verified by specialists and corroborated by prior research. The inputs included the sum of unoccupied beds, the level of importance or severity of the department, the number of vacant beds, the sum of skilled and capable nurses, the choice of task allocation based on the patient's medical condition or pathology, the LOS, the sum of ambulances leaving or departing from a location, the process of admitting a patient to a hospital for medical care and treatment, the rate at which patients are moved or transferred to different hospital units or facilities after being admitted, the time taken for ambulance personnel to transfer a patient from the ambulance to the hospital or medical facility, the presence or accessibility of medical apparatus or devices for use, and the number of proficient or capable physicians. However, this study concentrated on two specific outcomes: the impact on the patient's quality of life and the number of patients who have received medical care or treatment. Using the analytic hierarchy process (AHP) as one of the MCDM techniques, the study measured the weight of efficiency factors to achieve more precise aggregation outcomes, considering the level of contradiction between criteria values. The findings indicated that half of the hospitals (ten out of twenty) demonstrated efficient service in their EDs whereas the remaining ten hospitals showed lower levels of efficiency.

Gharahighehi et al. (94) proposed a methodology to improve the performance of a hospital's ED in Iran. The ED faced challenges due to extended waiting times and uneven resource allocation, causing issues for both patients and ED staff. To address this, the method involved simulating the patient flow within the ED, assisted by DEA-DES, to identify the bottlenecks responsible for the inefficiencies in ED performance. The simulation model considered non-homogeneous patient arrivals and provided detailed representations of diagnostic procedures, including medical conditions through the study and examination of bodily samples or specimens, test center testing, a medical imaging technique that uses high-frequency sound waves to create visual representations of internal body structures in a non-invasive manner, magnetic resonance imaging (MRI), CT scan and radiology. DEA software was applied to analyze ten different scenarios, each consisting of one input and three outputs. In this context, each scenario represented a DMU. The input was the average number of patients arriving per day. The initial output was the amount of left without being seen (LWOS) patients, the second output was the average waiting time, and the third output was the cost. To evaluate efficiency, all outputs were normalized using an output-oriented approach. Among the ten scenarios, four were considered efficient, achieving a maximum efficiency score of one. However, the remaining six scenarios were deemed inefficient and required adjustments or replacements. Four well-known MCDM techniques including DEA, AHP, VIKOR, and Delphi method were applied in this study. DEA was employed to identify efficient scenarios, while AHP was used to assign weights to every individual principle. The Delphi method was applied to determine appropriate rates of usage for different resources. Additionally, the prolonged VIKOR method was used to assess and rank data on 95% confidence intervals obtained from efficient scenarios based on divergent factors. Finally, by applying the highest-ranking setting, which did not require any additional investments, the overall waiting time for acute patients could be reduced by approximately 5%.

2.3.5 Applying Various DEA Models for the Management of Stroke Emergency Conditions

DEA has been used in stroke in some studies. The initial study about stroke was suggested by Ozcan et al. in 1998 (95). They applied CRS input-oriented DEA to analyze relations among contributors' knowledge and technical efficiency. The four inputs considered in this study were average LOS, charges for occupational therapy (OT) and physical therapy (PT), as well as total charges. All three variables served as measures of resource usage. Health administrators, who were refunded based on the diagnosis related group (DRG) system, had strong incentives to reduce the average LOS while maintaining quality outcomes. Therefore, a lower LOS indicated higher productivity under similar circumstances. To analyze the outputs, they were divided into two categories to consider different patient case mixes: mild and severe. Severe strokes were identified by either a coma diagnosis or having at least four diagnoses with at least one surgery performed to treat the principal diagnosis directly. The number of secondary diagnoses had been verified as an indicator of severity in studies of other medical procedures. All cases that did not meet these criteria were classified as mild stroke cases. The charge variables represented the resources required for stroke treatment. Although using true costs would have been a more accurate measure of resource usage, the necessary data was not available. As a result, it was assumed that charges reflected the level of resource utilization in the analysis. The article examined the average LOS and the expenses related to physical therapy for cases of stroke, which were classified as mild or severe, across 214 hospitals categorized by their level of experience in stroke treatment. These factors were used as input variables in the study. This study found that, on average, technical efficiency develops with experience. Conversely, although more qualified suppliers were considered more technically efficient on average, they tended to charge more. The study further suggested that the gap in the case of acuteness among efficient and inefficient contributors expands as the experience level increases. The suggested outcomes indicate a significant ability for workers who are not operating efficiently to change methods of practice to those of related effective workers to decrease collective costs significantly.

Behr et al. (96) proposed health system efficiency at the country level based on the Organization for Economic Co-operation and Development (OECD) health data. 30-day mortality after admission to a hospital for ischemic stroke per 100 patients (based on admission data) and 30-day mortality after admission to a hospital for acute myocardial infarction (AMI) per 100 patients (based on admission data) were two specific outputs. Due to issues related to data availability and missing information, they were unable to include all aspects of the ideal-typical inputs. Instead, the inputs used in the study were categorized into three broader categories. The first category was basic medical inputs, which consisted of variables like the number of hospital beds for every 1000 individuals, the number of committed physicians for every 1000 individuals, and the number of committed nurses for every 1000 individuals. The second category was intermediate medical inputs, which included variables such as surgical procedure for cataracts, overall number of procedures for every 1000 individuals, surgical procedure for coronary artery bypass (the number of hospitalizations for every 1000 individuals), and kidney transplantation (the overall number of medical procedures for every 1000 individuals). The third category was financial inputs, which involved healthcare spending as a percentage of the GDP. They categorized the output indicators into two groups: designated and non-designated. Although they acknowledged the suggested categorization was not entirely precise, they considered designated outputs to be more directly associated with the impacts of the health system compared to the undesignated outputs. The designated outputs comprised the number of infant deaths per 1000 live births, the rate of mortality within 30 days after hospital admission for ischemic stroke as the number of deaths per 100 patients using admission data, and the rate of mortality within 30 days after hospital admission for AMI as the number of deaths per 100 patients using admission data. On the other hand, the non-designated output referred to life expectancy at birth. They emphasized numerous phases of healthcare approaches to detect inefficiencies: perfect evaluations of health systems, disregarding limitations on data access or data limitations, and the underlying theory or theoretical foundation for a discussion under real data limitations were among the highlighted phases. This information showed prospective policy involvements that could improve efficiency. Their analysis contained hospitals in 34 countries assisted by the VRS model. Productivity measures relative to average DEA prices were computed. Based on suggested data restrictions, they emphasized several aspects of each system rather than conducting a comprehensive analysis of each healthcare structure.

Another study suggested by Amiri (97) assessed the quality of nursing care. A cross-national study was conducted to analyze the responsibilities of recently graduated nurses in providing high quality nursing care and optimizing patient outcomes. This article considered the VRS model assisted by the statistical technique of a generalized linear model for stroke care services in Finland. Data was gathered from 33 OECD countries, encompassing the sum of nursing graduates for every 100,000 members plus three OECD health care quality indicators (HCQI) within the acute care centers. These HCQIs included the mortality rates within 30 days, both in-hospital and out-of-hospital, for every 100 patients incorporating AMI, hemorrhagic stroke, and ischemic stroke. Additionally, four control variables were included in the analysis: the sum of individuals who have completed their medical education and training, nurses currently working in the profession, and the distribution of doctors for every 1000 individuals (acting as substitutes or representatives for other various healthcare occupations), also, the sum of CT scanners per one million individuals (an indicator representing the level of healthcare expertise). Increased personnel or a larger workforce level of newly qualified nurses related to improved patient results in acute care, while the clinical efficiency of nursing graduates (which was linked to their educational level) was the critical reason for increasing the quality of DMUs and patient survival rates. Furthermore, integrating the DEA model with other linear or nonlinear programming approaches is important for DMU's evaluation. Conversely, one of the most difficult tasks in allocating resources within musculoskeletal rehabilitation units is providing treatment for patients with brain injuries, particularly those who have suffered a stroke or are in the post-stroke phase.

Koltai et al. (98) proposed output oriented SBM for assessing in-patient rehabilitation centers in Hungary. The four selected inputs in this study were the number of hospital beds (this refers to the overall bed capacity in recovery units, that establishes the main ability of these parts to deliver medical care provided to patients with musculoskeletal conditions), sum of medical doctors (this represents the full-time equivalent (FTE)), sum of doctors employed at the rehabilitation units, sum of nurses (this indicates the full-time equivalent number of nurses working within the rehabilitation part), and sum of medical practitioners with specialized expertise (this refers to the full-time equivalent number of various specialized healthcare professionals such as verbal communication therapeutic services, mental health professionals, certified massage therapists, instructors specialized in acceptable education, physical therapists ,physical therapists assistants, professionals in the field of healthcare who assist individuals in acquiring or restoring the abilities necessary for their daily activities and tasks, healthcare professionals who focus on the management and care of orthopedic devices and equipment, including braces, casts, and prosthetics, professionals who provide support and assistance to individuals, healthcare professionals who specialize in providing physical education and exercise programs tailored to individuals with medical conditions or special health needs, educators who work with students with special needs, healthcare professionals who specialize in nutrition and dietary advice, and other professionals who provide various forms of therapeutic treatment). In addition to using operating expenses and investment factors, the researchers also attempted to consider the financial aspect. However, obtaining accurate and comparable data for these financial inputs is a big challenge. As a result, the primary mode of financing for hospital units relied on the sum of beds. Therefore, the sum of beds was applied as an approximation for the impact of financial inputs. Four outputs were the number of patients (this represents the quantity of musculoskeletal patients who are discharged from the department either their therapeutic or recovery-oriented care is completed or due to transmission to other healthcare units), a typical alteration in health condition (this indicates the typical variance in the Barthel index (BI) score at the time of admission compared to the score when leaving the hospital. It reflects the change in health status during the rehabilitation period), the quantity of individuals with stroke and brain injuries (this value indicates the amount of the population with complex cases among all patients), hypothetical potential for patients to improve their health status (this represents the average variation among the highest amount of the BI upon admission). The value is obtained by subtracting BI from 100 and indicates the possible enhancement in the health condition that individuals can experience throughout their rehabilitation journey). As a result, the research focused on those rehabilitation centers that concentrate on patients recovering from stroke or other brain damage. The main result was the patients' health condition change in efficiency score. Assessing the impact of hospital services on health improvement often proves challenging to quantify. Still, this determination is needed to connect the availability of DEA studies with the needs of decision-makers seeking DEA results.

Finally, despite the potential advantages of using operation research (OR) methodologies in the healthcare industry, there exists a notable lack of research regarding the application of OR tools like MOLP in addressing complex healthcare challenges, particularly in the assessment of stroke care services. Moreover, although existing literature emphasizes the benefits of providing appropriate care services to stroke patients, it falls short in demonstrating over an extended period advantages of enhancing the instant availability of different stroke care interventions for patients' accessibility throughout their lifetimes. Consequently, a recent study proposed by Mirmozaffari et al. (99) aimed to address this significant research gap by filling it with valuable insights and information. They suggested a novel integrated approach to stroke care services. DEA and MOLP are extensively utilized for evaluating efficiency. Even with their similarities and overlapping principles, they have developed independently. The generalized DEA (GDEA) cannot consider decision makers' (DM's) individual choices and past efficiency records. On the other hand, MOLP can include the DM's preferences when making decisions. To address this limitation, they transformed the GDEA to MOLP using the maximum-ranked option, leading to several advantages of interactive problem-solving, integration of the step method (STEM) to reflect DM's choices, elimination of the need for pre-established preference information, and application of the most preferred solution (MPS) to determine the most effective method or strategy. This paper has the potential to serve as a starting point for various research directions. One such area involves expanding the practical use of the non-radial or non-oriented GDEA model. Additionally, an interesting subject for investigation pertains to exploring the robust inverse GDEA and comprehensive framework of the interactive GDEA dual model and MOLP. However, it's worth noting that the data for GDEA might be imprecise during production activities. Therefore, it becomes essential to consider the concept of imprecise interactive GDEA.

2.4 Discussion and Limitations

Despite significant efforts to enhance the performance of EDs, there remains a need to further develop cutting-edge solutions for implementation within the emergency care environment. Accompanied by timely external measures, efficient emergency care networks must be established in real-world scenarios. These strategies could also be adapted and applied to support ED operations beyond the pandemic period. For instance, the integration of DEA, machine learning, and simulation techniques, which are currently used to predict health outcomes for ED patients, could also be utilized to anticipate potential health issues in individuals suffering from acute ischemic stroke and AMI. Moreover, the strategies devised to enhance resource allocation and patient flow can be embraced by EDs to manage surges in demand, which are anticipated due to population growth and potential new epidemics/pandemics. Diversely, the methodologies proposed here could be extrapolated to various healthcare settings like hospitalization, surgery, and intensive care. For example, simulation techniques might be employed to predict mortality rates, LOS, and the probability of discharging patients to their homes. DEA could also model patient pathways and treatment alternatives within these services, optimizing the utilization of available resources. Similarly, expanding DEA projects could ensure adherence to healthcare and safety protocols, establishing a foundation for comprehensive data collection and performance analysis in these units.

There are certain limitations to this review. Firstly, the process improvement approaches discussed primarily pertain to the realm of industrial engineering. Considering methodologies beyond this scope, such as clinical management units (CMUs) and clinical-related interventions, could be valuable. Secondly, financial outcomes could be factored into the analysis, potentially constraining the applicability of the described approaches in EDs operating within budget constraints, especially those in low and middle-income countries. Thirdly, despite a carefully implemented and monitored review process, there is a possibility that some relevant studies were inadvertently excluded. Next, valuable insights may have been missed due to the exclusion of the grey literature in the evidence search. Finally, we were unable to address all the other advanced methodologies within MCDM and DEA that have been utilized for diverse objectives. These encompass approaches like DEA fuzzy window analysis (100-101), dynamic DEA (102), the Russell model (103), as well as fuzzy MCDM techniques applied to assess the evaluation dimensions during the COVID-19 pandemic (104-106). Furthermore, well-known MCDM methods such as the technique for order of preference by similarity to ideal solution (TOPSIS), and decision-making trial and evaluation laboratory (DEMATEL) were also applied to categorize significant human error factors in EDs (107-111).

2.5 Conclusion and Future Studies

This narrative review contributes to DM's skills in ED performance improvement to recognize the advantages and drawbacks of DEA. A major benefit is its broad range and all-encompassing approach, effectively bridging the gap between health economists, health services researchers, and DMs in acute care. We identified several crucial aspects to consider when applying DEA studies in stroke and acute care centers. In addition to incorporating these parameters, DEA applications must ensure reproducibility and transparency in both the methodology and results. Researchers are advised to collaborate and work together to enhance the consistency of efficiency measures and maximize the usefulness for consumers. Additional research is required to address the gaps in certain performance measurements, such as incorporating health outcomes as outputs or capital resources as inputs. Furthermore, there is a need to explore the reasons behind productivity changes, their decomposition, and the factors contributing to improved performance in the delivery of EDs services. Moreover, developing the application of sensitivity tests is essential to investigate how variations in the DEA model can contribute to uncertainties in the efficiency results. DEA in EDs should put more attempts into improving the precision of the research outcomes by measuring the sensitivity analysis. Only a subset of articles has utilized methodologies to enhance the model requirements, such as selecting appropriate inputs and outputs, incorporating weight restrictions to account for value judgments in DEA modeling, employing super efficiency models to handle outlier observations, and thus providing DMs with more dependable information. However, we conducted a comprehensive evaluation of the methodological configurations used in the papers, providing in-depth explanations concerning the models applied, selected inputs, outputs, and all pertinent methodologies. Finally, we investigated multiple approaches to improve DEA's standing, shifting it from a simple technical application to a strong methodology that can be effectively employed by healthcare managers and decision-makers.

In the future study, one example within the acute management of stroke will be the application of DEA to benchmark the performance of community hospitals to enhance the number of stroke patients who meet the eligibility criteria and receive advanced treatment with EVT requiring transfer while reducing the number of futile transfers of patients who are ineligible for treatment upon arrival. This approach is also suitable for implementing in cases of prompt thrombolysis and PCI for AMI or heart attack. There is also a lack of research studies that apply DEA to evaluate the performance of acute stroke and AMI systems of care. Specifically, DEA can be used to evaluate different EDs' performances to assess the proportion of patients that are treated in both conditions. The proportion of patients that receive treatment is often affected by the population that it serves (e.g., age), the size of the hospital, and the proximity to a large comprehensive center, which provides an opportunity for the application of DEA to provide an efficient frontier that benchmarks this important measure for various hospitals.

2.6 Author Contributions

Methodology, N.K, and M.M.; Conceptualization, M.M., and N.K.; Investigation, M.M.; Resources, M.M., Writing—Original Draft Preparation, M.M.; Writing—Review and Editing, N.K.; Visualization, M.M., and N.K.; Supervision, N.K.; Project Administration, N.K. All authors have read and agreed to the published version of the manuscript.

2.7 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Chapter 3: Study 2- An Optimization Model for Transferring Ischemic Stroke Patients for Endovascular Thrombectomy Using Data Envelopment Analysis

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Journal: Healthcare Analytics (Elsevier)

Publication Status: Under Review (Submitted on 7 December 2023).

Student Contributions: Methodology M.M.; Conceptualization, M.M.; Investigation, M.M.; Resources, M.M., Writing—Original Draft Preparation, M.M.; Visualization, M.M.

3.1 Abstract

Background: This study applies data envelopment analysis (DEA) to optimize transfer times and futile transfers of eligible ischemic stroke patients receiving endovascular thrombosis (EVT) in primary stroke centers (PSC) in Nova Scotia. The study aims to assess healthcare delivery in Nova Scotia over two periods. It seeks to improve stroke care for rural populations by examining nine inputs, including age and distance between PSCs and the Comprehensive Stroke Centre (CSC) that provided EVT treatment, in relation to a single output variable: whether EVT is performed or not.

Methods: In the first phase, 115 patients were treated as decision-making units (DMUs) for ten PSCs through an application of an input-oriented variable returns to scale (VRS) assisted by super efficiency analysis using the Python-based PyDEA tool. This tool is known for its unrestricted capacity in handling DMUs, inputs, and outputs. In the second phase, eight PSCs with low patient numbers were merged into four DMUs, each consisting of two PSCs. These two merged PSCs have a limited number of patients, and the selected PSCs are also geographically close to one another. Two PSCs have been kept separate because they had sufficient patient volume. In the first phase, VRS generated more reasonable efficiency scores for evaluation, while in the second phase, constant returns to scale (CRS) outperformed VRS, yielding better results. In the initial stage of the second phase, ten PSCs were considered as six DMUs using the input-oriented CRS and VRS for 115 patients. Super-efficiency measures were applied in this stage to improve the evaluation process further. In the second part of the second phase, a comparison between the first period (2018-2019) and the second period (2020-2021) was conducted using the Malmquist productivity index (MPI) considering CRS and VRS to evaluate the relative efficiency and productivity change of six DMUs over time.

Results: Due to PyDEA's limitations in MPI evaluation over time, a different software namely, Probability-Imprecise DEA (PIM-DEA) was employed, which provided the required advanced functionalities. Finally, the results of both phases highlighted the detrimental effect of considerable distances between certain PSC and the CSC, the sole facility equipped with EVT technology in the selected small province in Canada, leading to increased access times for receiving EVT.

Conclusion: One significant constraint arises from the relatively small size of the province under examination. This size constraint inevitably leads to a more restricted pool of available data. As a result, it became necessary to combine several PSCs to bolster patient sample sizes.

Keywords: data envelopment analysis; endovascular thrombectomy; variable returns to scale; constant returns to scale; Malmquist productivity index; super efficiency.

3.2 Introduction

In healthcare, DEA can be applied to assess and optimize the performance of healthcare facilities, such as hospitals, in terms of resource utilization and service delivery. In the context of stroke care, DEA can be used to assess the efficiency of hospitals in providing EVT, considering factors like patient throughput, resource allocation, and quality of care. This emphasizes the need for tools like DEA to assess and optimize the performance of healthcare facilities, ensuring they can deliver essential services efficiently, even during times of crisis. DEA can help identify areas for improvement in resource allocation and policy formulation, ultimately enhancing stroke care and other critical healthcare services. This contribution is also novel as we are applying it to Nova Scotia which has a unique geography with long driving distances compared to flight distances and where a large portion of its population live outside of the main city, which has the province's only EVT-capable hospital. So, this paper has significant potential benefits to expanding scientific knowledge to health systems facing similar issues as Nova Scotia.

In this study, two specialized software applications have been utilized to facilitate the analysis:

1. In the initial scenario, wherein the dataset encompasses 115 DMUs representing individual patients, PyDEA was employed. This choice was motivated by the notable advantage offered by PyDEA, operating within the Python programming environment, which allows for the handling of an extensive number of DMUs, inputs, and outputs without constraints. PyDEA, short for Python-based DEA, is a software tool designed for conducting DEA using the Python programming language. It offers a flexible and powerful environment for assessing the relative efficiencies of DMUs in various contexts, including healthcare.
2. Subsequently, in the second scenario involving a specific set of DMUs, namely 10 PSCs, PIM-DEA was selected as the analytical tool. This decision was prompted by the absence of Malmquist evaluation functionality within PyDEA and the manageable number of DMUs associated with DASH. By leveraging PIM-DEA, the model could be effectively applied to yield insightful results. PIM-DEA is a specialized software tool used for conducting DEA when there is uncertainty or imprecision in the data. It's particularly useful when data is expressed in terms of probability distributions or intervals, allowing for more robust efficiency assessments.

These two software tools offer complementary functionalities, with PyDEA providing a versatile environment for large-scale DEA analyses, and PIM-DEA addressing scenarios where imprecise data is a crucial consideration. Together, they enable a comprehensive assessment of healthcare efficiency in the context of stroke care.

In Nova Scotia, there are 11 stroke centers throughout the entire province, with only one of them having the capability to provide treatment for stroke patients via EVT. In cases where ischemic stroke patients are located beyond the catchment of CSC, they will be transported to a PSC. Should patients meet the eligibility criteria for EVT, the PSC promptly facilitates their transfer to CSC. This procedural framework reflects the approach not only in Nova Scotia but also in analogous regions across Canada and internationally, where it is imperative to urgently transfer ischemic stroke patients to hospitals equipped for the EVT procedure.

The identification primary stroke center has been deliberately omitted to safeguard confidentiality and privacy. In Figure 1, the Nova Scotia Health Authority Management Zones are illustrated. Each zone—Western, Northern, and Eastern—features three PSCs represented by different numbers. The central zone, uniquely, hosts only one PSC (number 8), positioned in proximity to the sole CSC located centrally and indicated by yellow cross. In the second phase, eight PSCs with low patient numbers were merged into four DMUs, each consisting of two PSCs (PSCs number 5 and 10, 1 and 6, 3 and 4, 2 and 7). These two merged PSCs have a limited number of patients, and the selected PSCs are also geographically close to one another. Two PSCs have been kept separate because they had sufficient patient volume (PSCs number 8 and 9).

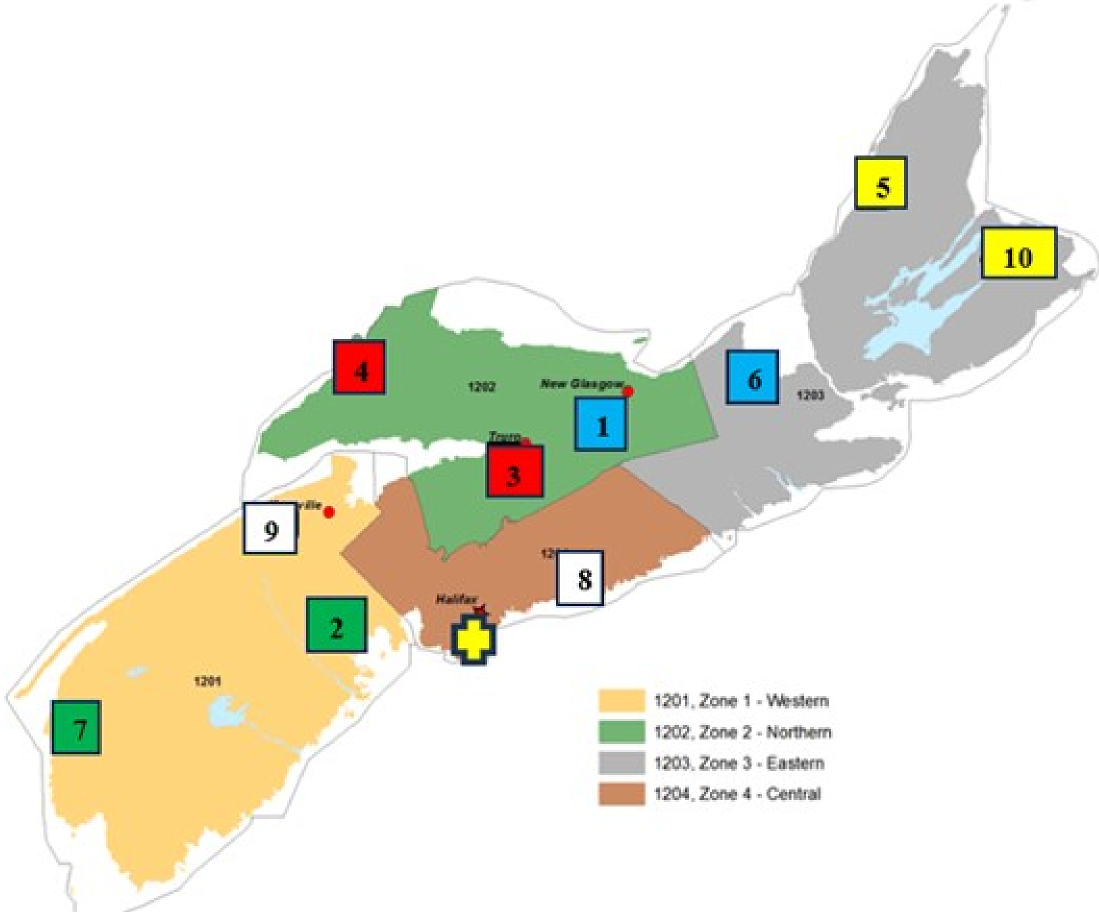

Figure 2: Stroke Centres Across Nova Scotia: The PSCs and the Only CSC Indicated by Numbers Including, Three PSCs in the Western Zone, Three PSCs in the Northern Zone, Three PSCs in the Eastern Zone, and Only One PSC in the Central Zone. The Only CSC in Nova Scotia in Central Zone Indicated by Cross. (PSC: Primary Stroke Centre; CSC: Comprehensive Stroke Centre).

3.3 Methods

Methods in this study contain the following seven subsections:

3.3.1 Proposed Framework of the Suggested Approach

The analysis in this study followed a systematic nine-step process in Figure 3. In the initial stage of data preprocessing, we prioritize the critical step of preparing the data. This involves a tailored approach based on the unique characteristics of the dataset.

Figure 3: Proposed Framework of Suggested Approach in This Study in Nine Steps*.*

In the overall data preprocessing, four essential steps were followed. In the first part, filtering reduced the data from 5156 patients to 115 during 2018-2021 (discussed further in subsection 3.7.3 Data Sources: Provincial Registry and Manually Imaging). In the second part, we employ either the mean, providing a measure of central tendency, or the median, a robust indicator that accommodates skewed distributions. This strategy proves invaluable in addressing missing data or 'nan cells,' ensuring the integrity and reliability of our analytical process. As a third step, before conducting DEA, categorical variables like sex, occlusion location, and collateral status were removed because DEA specifically analyzes continuous data. In the decision tree for variable inclusion in DEA, the process begins by categorizing variables into two main types: Categorical (Qualitative) and Numerical (Quantitative). Within the Categorical category, further distinction is made between Nominal variables (with no order ranking, such as mutually exclusive categories like Gender or specific areas in occlusion locations) that should be excluded from DEA, and Ordinal variables (with a clear order, like ASPECTS or Collateral quality) that can be included in DEA. On the Numerical side, both Discrete variables (e.g., counts like the number of EVT performed or thrombolysis given) and Continuous variables (e.g., age, time intervals, Euclidean distance, and driving distance) are deemed suitable for inclusion in DEA. This structured decision-making process ensures that only variables compatible with DEA requirements, whether categorical or numerical, are considered, contributing to the effectiveness and appropriateness of the analysis.

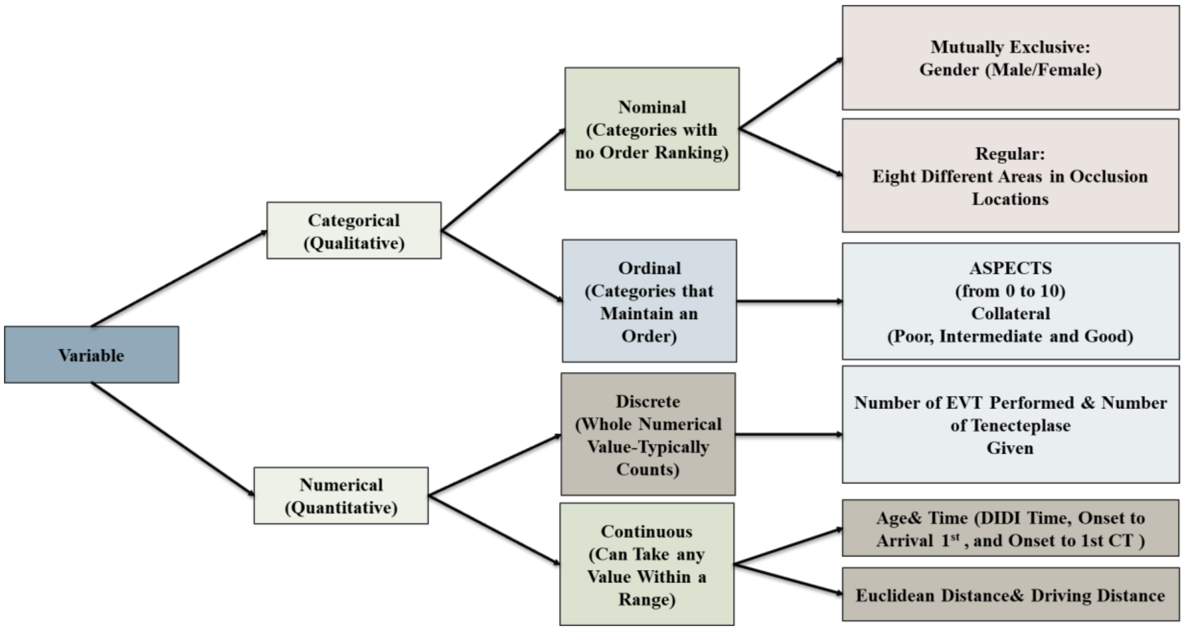

Figure 4: The Third Part of Data Preprocessing: Removing Nominal Categorical Variables in DEA Evaluation

In the fourth or final part of data preprocessing, before normalization (second step) in an input-oriented DEA, when we need to reverse benefits to costs, the specific approach we are referring to is often called "Data Transformation." This transformation is necessary when some inputs or outputs are considered desirable to maximize (benefits), while others are considered undesirable to minimize (costs). The transformation is typically applied to convert all inputs and outputs into a common dimension, usually by turning desirable outputs into costs or undesirable inputs into benefits. This ensures that the DEA model can be consistently applied to either maximize benefits or minimize costs. For inputs that are initially considered as benefits (desired to be maximized), we may apply a reciprocal transformation to convert them into costs. It is to take the reciprocal of the value for inputs considered as benefits. We apply reciprocal of the value for two inputs of Alberta Stroke Program Early CT Score (ASPECTS), and Collateral to change them to costs, like other inputs, and finally apply input-oriented by minimizing all inputs. After applying the appropriate transformation to our inputs and outputs, we can then proceed with the normalization step. Normalization is crucial to ensure that the data is on a comparable scale before running the DEA model. So, in the normalization part, the data underwent Min-Max Scaling, normalizing it to a range between 0 and 1. Third, nine carefully selected inputs including Age, ASPECTS, Collateral, thrombolysis given, onset to Arrival at PSC time, onset to 1st CT time, arrival to PSC to arrival to CSC Time (Door-In-Door-In Time), Driving Distance, and Euclidean Distance were identified, with the sole output being whether EVT was performed. In our study, we conduct a thorough comparative analysis between two parts: one incorporating Age, ASPECTS, and Collateral inputs and the other excluding them from consideration. This dual approach, guided by our input-oriented VRS and VRS super-efficiency DEA model, allows for a nuanced exploration of the impact of these inputs on efficiency scores. The first part, encompassing all inputs, establishes a baseline understanding of efficiency outcomes influenced by Age, ASPECTS, and Collateral. In contrast, the second part excludes these factors, focusing solely on time and distance-related inputs aligned to minimize transfer time in stroke care. The comparative analysis, detailed in the results section, illuminates the differential efficiency landscapes under these two parts, providing insights into the role of Age, ASPECTS, and Collateral in optimizing stroke care processes. The main inputs that significantly influence and have both positive and negative effects on efficiency in our DEA model include thrombolysis given, onset to arrival at PSC time, onset to the 1st CT time, arrival to PSC to arrival to CSC time (Door-In-Door-In Time), driving distance, and Euclidean distance. These variables encompass critical aspects of the process under evaluation, reflecting the administration of thrombolysis, time intervals in the patient care pathway, and the spatial aspects related to driving and Euclidean distances. By including these inputs in our analysis, we aim to comprehensively capture the factors impacting efficiency in the context of our study, recognizing both favorable and unfavorable influences on the overall effectiveness of the evaluated units. Step four and in the initial phase, 115 patients were treated as independent DMUs, applying an input oriented VRS method aided by super-efficiency analysis to address the issue of a significant quantity of DMUs having an efficiency score of one. Given the large dataset, the Python-based PyDEA tool was employed for its capacity to handle a substantial number of DMUs, inputs, and outputs. Subsequently, in the fifth step or the second phase, eight PSCs with low patient volumes were merged into four DMUs, each comprising two hospitals, based on their proximity and low patient count. Two hospitals or PSCs were kept separate due to their higher patient volume, resulting in a total of six DMUs. In the second phase, CRS outperformed VRS, providing more reasonable efficiency scores. Furthermore, in the eighth step, a comparison between two time periods (2018-2019 and 2020-2021) was conducted using the MPI with a focus on CRS to assess the relative efficiency and productivity changes of the six DMUs over time. To fix PyDEA's time evaluation issues, in the last step, we used a different software. In the second part of the second scenario, we used PIM-DEA because it has better features and fits our needs.

3.3.2 Endovascular Thrombectomy and the Process of Determining Endovascular Thrombectomy Eligibility in Nova Scotia

EVT is a specialized procedure that removes brain blood clots via specific tools such as aspiration or stent retrievers. Ischemic stroke patients with LVO are eligible for EVT as the clot is in a large vessel that is accessible to retrieve. Ischemic stroke patients with an LVO are typically the most severe ischemic stroke patients, and they account for 30-40% of ischemic stroke cases (9). There are 10 PSCs in Scotia, and if a patient eligible for EVT arrives at the PSC, swift transfer to a CSC is crucial for timely EVT treatment.

To conduct EVT, a specialized guide for example a balloon catheter is carefully placed into the femoral artery, typically situated near the thighs. This guide is then meticulously advanced through the circulatory system until it reaches the internal carotid artery, which extends through the neck. The use of angiography during this process grants the neurosurgeon a clear visual of the blood vessels, ensuring precision. Following this, a micro-catheter, accompanied by a micro-wire, is delicately introduced into the brain, navigating beyond the clot. Once the micro-wire successfully reaches the heart of the clot, the attending physician proceeds to gently extract it. Upon successful removal of the clot through a careful suctioning process, the doctor then conducts a thorough assessment to confirm that the blood flow has been fully restored to its normal state, ensuring the effectiveness of the procedure. The catheter is subsequently eliminated, and targeted pressure is used at the insertion site to staunch any potential blood loss (112).

In the process of determining EVT eligibility, a patient first arrives at the hospital or is transported by ambulance. Subsequently, a physician conducts an initial assessment to confirm a stroke diagnosis and evaluate the stroke's severity. Neuroimaging evaluation follows, involving a Non-Contrast Computed Tomography (NCCT) scan of the head to ascertain the stroke type (Ischemic or Hemorrhagic), with the ASPECTS providing a score for the extent of cerebral damage due to the stroke. For Ischemic Stroke patients eligible for treatment, thrombolysis is administered to dissolve the clot. To determine EVT eligibility, patients undergo additional imaging using CTA to precisely identify the clot's location within the cerebral vasculature. mCTA and, if possible, CT Perfusion (CTP) scans are performed concurrently after the NCCT. mCTA provides cerebral angiograms in three distinct phases, offering critical information about collateral blood flow. The CTP scan plays an important role in distinguishing between salvageable and irreversibly damaged sections of the brain. This differentiation is crucial in determining the potential benefit of EVT, ensuring that eligible patients receive optimal treatment for an increased likelihood of a successful outcome. As depicted in Figure 6, the eight steps involved in the process of determining EVT eligibility are demonstrated.

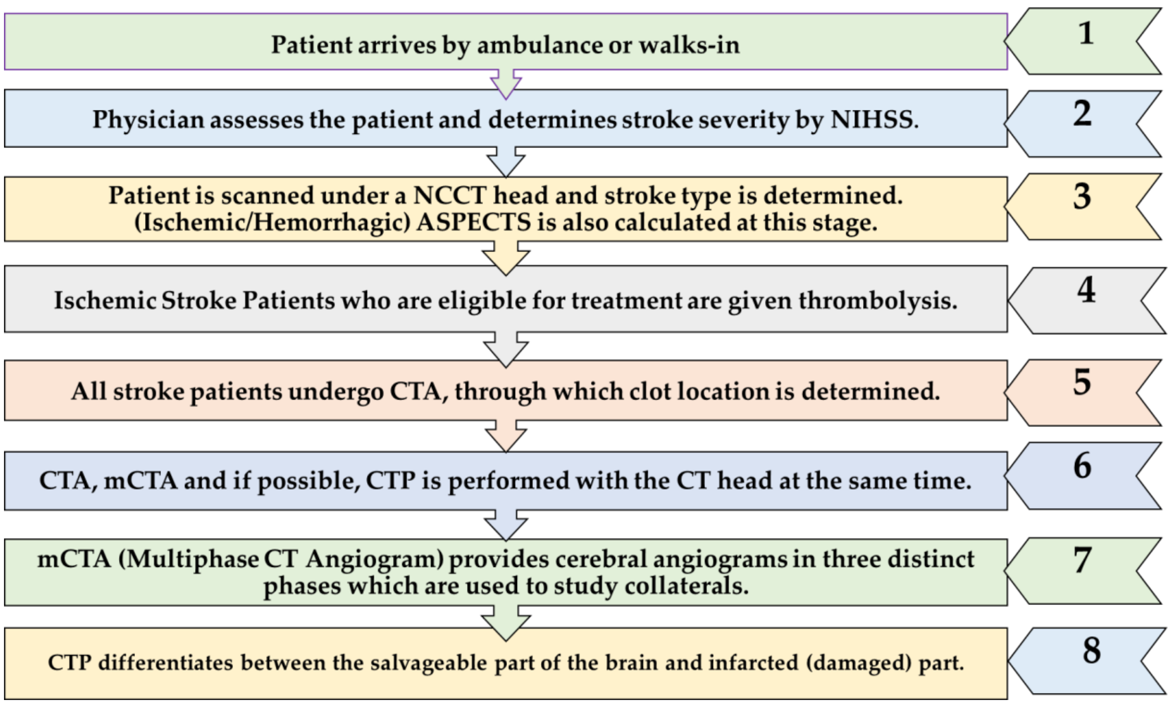

Figure 5: The Process of Determining Endovascular Thrombectomy Eligibility in Eight Steps.

Using the various imaging scans (NCCT, (m)CTA, CTP), EVT eligibility is determined between the local emergency physician at the PSC and the neurologist and interventional neuro-radiologist. If the patient is deemed eligible for EVT, urgent transfer to the CSC from the PSC is arranged. The transport team determines if they can deploy a helicopter or if they will use a ground ambulance. The time to deploy the team can be optimized through parallel workflow.

3.3.3 Return to Scales, Input-oriented, Output-oriented and the Analysis of Weakly Efficient Decision-Making Units for Basic Data Envelopment Analysis Models

In this study, we applied DEA, considering patients (in the first phase) and hospitals (in the second phase) as DMUs, subject to evaluation based on their efficiency in utilizing resources for healthcare outcomes. For patients, this involves assessing the effectiveness of healthcare resources in achieving positive health outcomes. Hospitals, on the other hand, are evaluated based on factors like staffing, equipment, and finances, in relation to the delivery of quality healthcare services. In this study, the evaluation of efficiency involves a specific set of metrics. For both patients and hospitals, the analysis considers eight different inputs—these likely encompass various resources, factors, or variables relevant to healthcare delivery. Additionally, the study focuses on one key output, namely whether EVT was performed or not. This choice of inputs and output serves as the basis for assessing the efficiency of resource allocation and decision-making in both patient and hospital contexts.

DEA represents an approach to measuring relative efficiency in situations involving multiple inputs and outputs that cannot be directly compared. In such cases, efficiency is determined by calculating the weighted sum of outputs divided by the weighted sum of inputs. In mathematical notation, Bousssofiane et al. (113) create the DEA model as a fractional linear setup with the structure presented below:

$$\boldsymbol{TE_0 = Max\frac{\sum_{r=1}^{s} U_r y_{rj0}}{\sum_{i=1}^{m} V_i x_{ij0}}} \qquad \textbf{(1)}$$

$$\boldsymbol{St.\ \frac{\sum_{r=1}^{s} U_r y_{rj}}{\sum_{i=1}^{m} V_i x_{ij}} \leq 1, \quad j = 1, \ldots., n;}$$

$$\boldsymbol{U_r, V_i \geq \varepsilon; \quad r = 1, \ldots, s,\ i = 1, \ldots. m}$$

$\boldsymbol{TE_0}$ represents the technical efficiency score for DMU $\boldsymbol{j0}$. $\boldsymbol{U_r}$ signifies the weight assigned to output $\boldsymbol{r}$, where $\boldsymbol{r}$ ranges from 1 to $\boldsymbol{s}$ ($\boldsymbol{s}$ being the total number of outputs). $\boldsymbol{V_i}$ denotes the weight attributed to input $\boldsymbol{i}$, with $\boldsymbol{i}$ ranging from 1 to $\boldsymbol{m}$ ($\boldsymbol{m}$ being the total number of inputs). $\boldsymbol{n}$ represents the total number of patients for the first scenario and total number of PSCs for the second scenario. $\boldsymbol{\varepsilon}$ is a small positive value. $\boldsymbol{y_{rj}}$ represents the number of output $\boldsymbol{r}$ generated by patient $\boldsymbol{j}$ in the first scenario or PSCs $\boldsymbol{j}$ in the second scenario. $\boldsymbol{x_{ij}}$ signifies the number of input $\boldsymbol{i}$ used by patient $\boldsymbol{j}$ or PSCs $\boldsymbol{j}$. $\boldsymbol{j0}$ specifically refers to the patients or PSCs undergoing assessment.

Figure 6 shows Return-to-Scale (RTS) areas including VRS, CRS, Increasing Return to Scale (IRS) and Decreasing Return to Scale (DRS), basic models, input-oriented (IO) and output-oriented (OO).

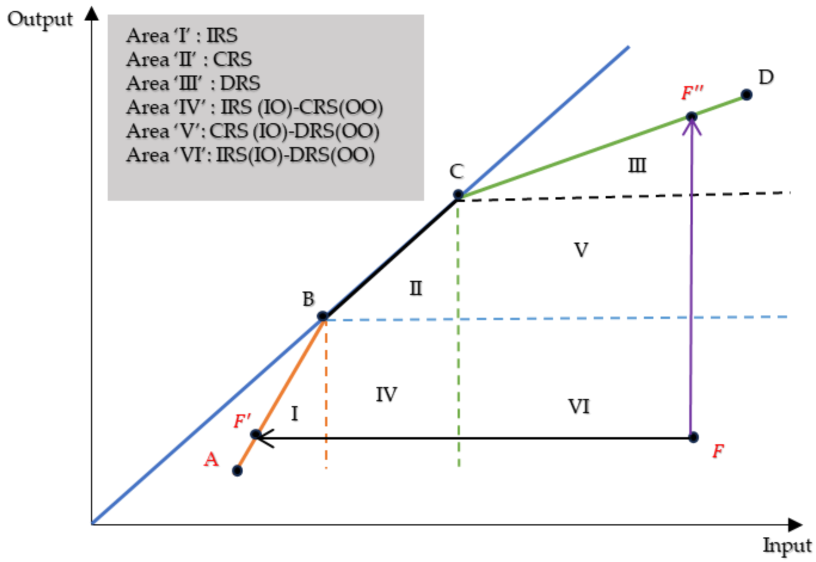

Figure 6: Six Return to Scale Regions.

The economic principle of RTS has been extensively examined within the DEA framework. Traditionally, RTS has been limited to single-output scenario. DEA broadens the concept of RTS to encompass cases with multiple outputs, thereby expanding the applicability of DEA.

In Figure 6, five DMUs labeled as A, B, C, D, and F are depicted. The OBC ray signifies the CRS frontier. AB, BC, and CD form the VRS frontier, representing CRS, IRS, and DRS, respectively. Both B and C demonstrate CRS attributes. On the AB segment, IRS dominates to the left of point B, while on the CD segment, DRS prevails to the left of point C.

For a non-frontier DMU denoted as F, when employing the input-oriented VRS envelopment model, F' becomes the optimal reference point, and the RTS classification for F is categorized as IRS. Conversely, when employing the output-oriented VRS envelopment model, F" is identified as the efficient target, and the RTS classification for F is categorized as DRS. Nonetheless, the areas corresponding to IRS, CRS, and DRS are individually defined regardless of the VRS model utilized. These are designated as Area I for IRS, Area II for CRS, and Area III for DRS. In fact, Figure 4 illustrates a total of six distinct RTS areas. The remaining areas, IV, V, and VI, are characterized by dual RTS classifications. Specifically, Area IV exhibits IRS in the input-oriented and CRS in the output-oriented. Area V demonstrates CRS in the input-oriented and DRS in the output-oriented. Finally, Area VI displays IRS in the input-oriented and DRS in the output-oriented.

As mentioned above, two alternative approaches including input-oriented and output-oriented are offered in DEA to evaluate the efficient frontier. The provided CRS model is characterized as an input-oriented model, aiming to minimize inputs while maintaining the outputs at their existing level.

$$\boldsymbol{\theta^* = Min\,\theta} \tag{2}$$

$\boldsymbol{st.}$

$\boldsymbol{\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0},\ ,i = 1, 2, \ldots, m;}$

$\boldsymbol{\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{i0},\quad ,r = 1, 2, \ldots, s;}$

$\boldsymbol{\lambda_j \geq 0\ ,j = 1, 2, \ldots., n}$

Since $\boldsymbol{\theta = 1}$ is a feasible solution, the optimal value in above (1), $\boldsymbol{\theta^* \leq 1.}$ Considering $\boldsymbol{\theta^* = 1}$ the current levels of inputs cannot be reduced (proportionally), showing that $\boldsymbol{DMU_0}$ (represents one of the $\boldsymbol{DMUs}$ under evaluation) is on the frontier. However, considering $\boldsymbol{\theta^* < 1}$, $\boldsymbol{DMU_0}$ is controlled by frontier. $\boldsymbol{\theta^*}$ shows the input-oriented efficiency score of DMU_0.

Sometimes, several $\boldsymbol{DMUs}$ can still reduce their inputs to reach the same efficient frontiers. The suggested $\boldsymbol{DMUs}$ are weakly efficient, and a reduction in individual inputs is termed input slack. Therefore, both input slack and output slack might happen in Model (2).

$$\boldsymbol{S_i^- = \theta^* x_{i0} - \sum_{j=1}^{n} \lambda_j x_{ij}\ , i = 1, 2, \ldots, m;} \tag{3}$$

$$\boldsymbol{S_r^+ = \sum_{j=1}^{n} \lambda_j y_{rj} - y_{r0}\quad ,r = 1, 2, \ldots, s;} \tag{4}$$

$\boldsymbol{S_i^-}$ and $\boldsymbol{S_r^+}$ are input and output slack variables. So, for determining the possible non-zero slack after solving it, the following CRS linear programming is solved:

$$\boldsymbol{Max \sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+} \tag{5}$$

$\boldsymbol{st.}$

$\boldsymbol{\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = \theta^* x_{i0}\qquad ,i = 1, 2, \ldots, m}$

$\boldsymbol{\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^+ = y_{r0}\qquad ,r = 1, 2, \ldots, s}$

$\boldsymbol{\lambda_j \geq 0\ ,j = 1, 2, \ldots., n}$

Figure 7 shows the five $\boldsymbol{DMUs}$ along with the segmented linear frontier.

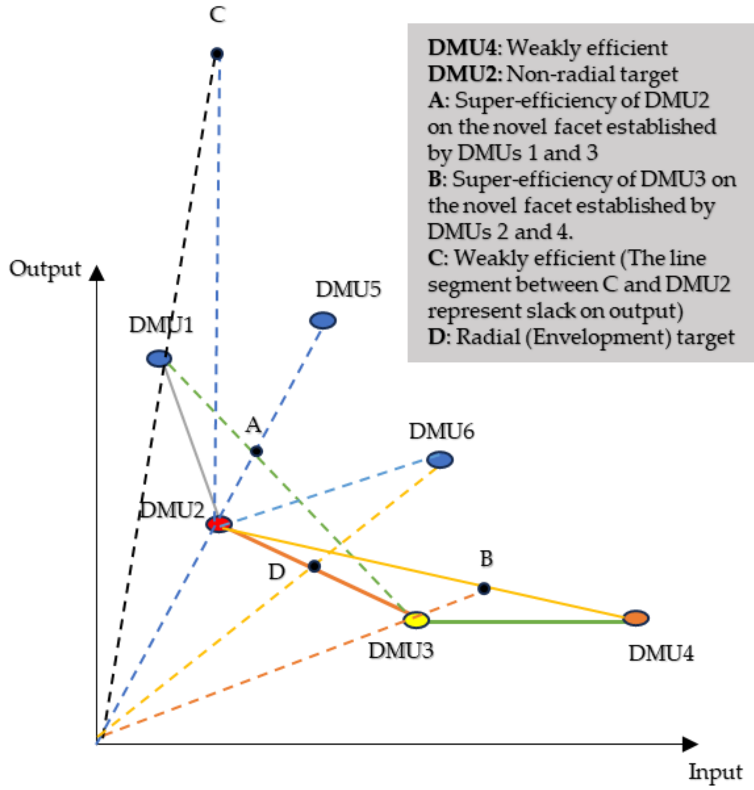

Figure 7: Weakly Efficient DMUs, Super-efficiency Model, Radial, and Non-radial DEA.

$\boldsymbol{DMUs}$ 1, 2, 3, and 4 lie on this frontier. It should be noted that $\boldsymbol{DMU4}$ is on the frontier. However, it can still reduce its input to reach $\boldsymbol{DMU3}$. This distinct input reduction is named input slack.

DMU_0 is efficient if and only if $\boldsymbol{\theta}^* = \mathbf{1}$ and $\boldsymbol{S_i}^{-*} = \boldsymbol{S_r}^{+*} = \mathbf{0}$ for all $\boldsymbol{i}$ and $\boldsymbol{r}$. In addition, DMU_0 is weakly efficient if $\boldsymbol{\theta}^* = \mathbf{1}$ and $\boldsymbol{S_i}^{-*} \neq \mathbf{0}$ and (or) $\boldsymbol{S_r}^{+*} \neq \mathbf{0}$ for some $\boldsymbol{i}$ and $\boldsymbol{r}$. So, in Figure 6, $\boldsymbol{DMUs}$ 1,2 and 3 are efficient and $\boldsymbol{DMU4}$ is weakly efficient.

Moreover, for the sake of streamlining computations and avoiding an infinite array of solutions (If (u^*, v^*) constitutes an optimal solution, then (au^*, av^*) remains optimal for any positive value of a, the previously mentioned fractional model (1) can be transformed into an input-oriented linear program in model 6. Finally, models (2) and (5) show a two-stage CRS model included in the following DEA model **(**22**)**.

$$\boldsymbol{Z_0} = \boldsymbol{Min\theta} - \boldsymbol{\varepsilon} \left(\sum_{i=1}^{m} \boldsymbol{S_i}^{-} + \sum_{r=1}^{s} \boldsymbol{S_r}^{+}\right) \qquad \textbf{(6)}$$

$st.$

$\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = \theta x_{i0}, i = 1, 2, \ldots, m$

$\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^+ = y_{r0}, r = 1, 2, \ldots, s;$

$S_i^-, S_r^+ \geq 0, \lambda_j \geq 0, j = 1, 2, \ldots, n \quad , \varepsilon \geq 0$

The transformation involves setting the total input weight to a fixed value of one to maximize the weighted sum of outputs. This ensures that the total output is maximized. This linear model is repeated multiple times to find the most efficient combination of input and output weights for each DMU. Typically, a DMU is considered efficient if it scores one, while a score below one indicates inefficiency.

The inclusion of non-Archimedean ε in the objective function of model (6) allows the minimization throughout θ to precede the optimization involving the slacks, S_i^- and S_r^+. Consequently, model (6) undergoes a two-step computation process, starting with the maximal reduction of inputs through the optimal θ^* in model (2); Subsequently, in the second stage, advancement toward the efficient frontier is reached by optimizing the slack variables in the model. (5). The existence of weakly efficient $DMUs$ leads to the existence of multiple optimal solutions. Therefore, if weakly efficient $DMUs$ are absent, we can skip the second stage calculation (model 5) and determine the slacks using models (3) and (4) instead. However, determining the presence or absence of weakly efficient is typically unknown in advance. It should be noted that incorporating $\sum_{j=1}^{n} \lambda_j = 1$ into models (2) and (5) transforms the CRS models into VRS. So, as a continuation of the previously mentioned CCR model, which operates under CRS, the input-oriented BCC model was introduced to incorporate the consideration of VRS (23).

$$Z_0 = Min\theta - \varepsilon \left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right) \qquad \textbf{(7)}$$

$st.$

$\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = \theta x_{i0}, i = 1, 2, \ldots, m;$

$\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^+ = y_{r0}, r = 1, 2, \ldots, s;$

$\sum_{j=1}^{n} \lambda_j = 1$

$S_i^-, S_r^+ \geq 0, \lambda_j \geq 0 \ \forall j, \varepsilon \geq 0, j = 1, 2, \ldots, n$

Dual variables (λ_j) represent shadow prices associated with constraints that limit the efficiency of DMUs to be not more than 1. When a constraint is restricted, the shadow price is typically positive; when it is nonbinding, the shadow price is zero. In the primal model solution, a restricted constraint indicates that the related $\boldsymbol{DMU_{j0}}$ possesses an efficiency score of 1 and a positive shadow price will be present. Hence, positive shadow prices in the primal model, or positive quantities for $\boldsymbol{\lambda_j}$ in the dual model, signify and identify the peer group for any inefficient unit. if a $\boldsymbol{DMU_{j0}}$ is efficient, the slacks will equal 0, and the efficiency ($\boldsymbol{Z_0}$) will equal 1. If $\boldsymbol{j_0}$ is inefficient, $\boldsymbol{Z_0}$ will be fewer than 1 and some slacks could be positive.

3.3.4 Super Efficiency Model

If a DMU being assessed is not part of the reference set in envelopment models, it leads to the creation of DEA models known as super-efficiency DEA models. The distinguishing feature of super-efficiency models, compared to envelopment models, is that the DMU_0 in assessment is deliberately left out of the reference set. In other words, super-efficiency DEA models use reference technology derived from all other $DMUs$ except the one under evaluation. The input-oriented CRS super-efficiency model is presented in the following model:

$$\boldsymbol{Min \quad \theta^{super}} \tag{8}$$

$$\boldsymbol{st.}$$

$$\boldsymbol{\sum_{j=1, j\neq 0}^{n} \lambda_j x_{ij} \leq \theta^{super} x_{i0}} \qquad \boldsymbol{, i = 1, 2, \ldots, m}$$

$$\boldsymbol{\sum_{j=1, j\neq 0}^{n} \lambda_j y_{rj} \geq y_{i0}} \qquad \boldsymbol{, r = 1, 2, \ldots, s;}$$

$$\boldsymbol{\lambda_j \geq 0 \; , j \neq 0.}$$

By incorporating the $\boldsymbol{\sum_{j\neq 0}^{n} \lambda_j = 1}$, into model (8), VRS is achieved. By incorporating the $\boldsymbol{\sum_{j\neq 0}^{n} \lambda_j \leq 1}$ NIRS is achieved. By incorporating the $\boldsymbol{\sum_{j\neq 0}^{n} \lambda_j \geq 1}$ NDRS) is achieved.

In Figure 7, when assessing the CRS super-efficiency of $\boldsymbol{DMU2}$, it is measured in comparison to point A on the novel facet formed by $\boldsymbol{DMUs}$ 1 and 3. If either $\boldsymbol{DMU4}$ or $\boldsymbol{DMU5}$ is excluded from the reference set, the frontier remains unchanged. Consequently, the super-efficiency score for $\boldsymbol{DMU4}$ and $\boldsymbol{DMU5}$ equals the input-oriented CRS efficiency score. Similarly, $\boldsymbol{DMU\ 3}$ is evaluated against point B on the new facet defined by $\boldsymbol{DMUs\ 2}$ and **4**.

If we evaluate the super-efficiency of $DMU1$. $DMU1$ is measured against C (see figure 7) on the frontier continued by $DMU2$. It can be observed that C is weakly efficient DMU in the continuing four $DMUs$ 2,3,4, and 5. So, the line segment between C and $DMU2$ represents slack on output. We want to modify such a super-efficiency score.

While super-efficiency models can distinguish the performance of efficient $DMUs$, it's important to note that these efficient $DMUs$ are not evaluated against a uniform benchmark. This is because the frontier, derived from the lasting $DMUs$, varies for each efficient DMU being assessed. Essentially, super-efficiency should be viewed as representing the ability for input reduction and output surpluses.

3.3.5 Malmquist Productivity Index

MPI is a method used to assess changes in productivity over time. Figure 8 shows CRS input oriented in MPI model.

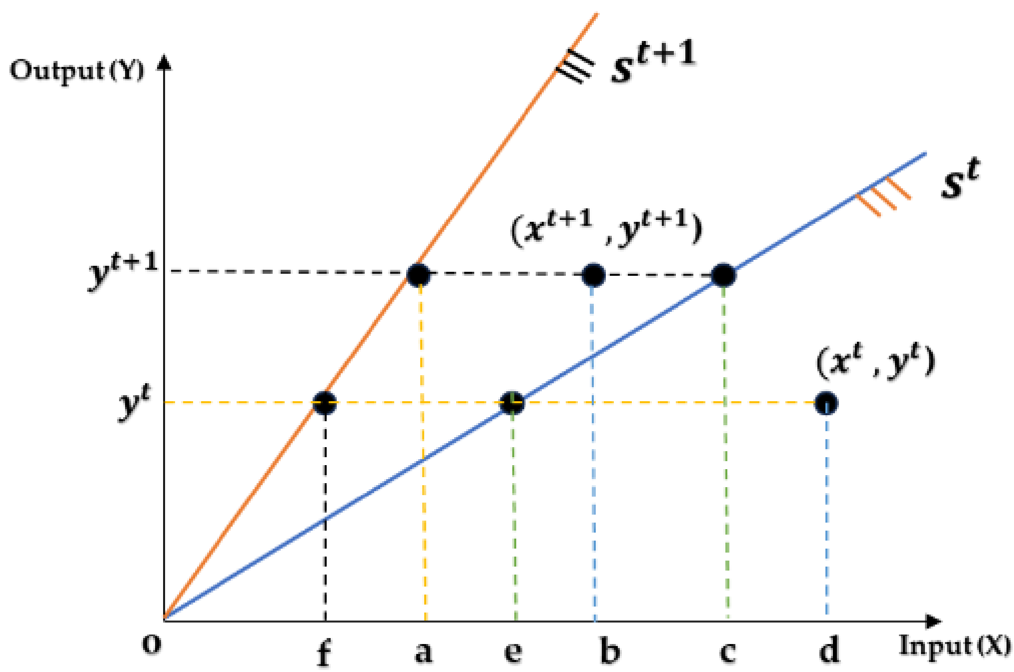

Figure 8: Constant Return to Scale Input Oriented Model in Malmquist Productivity Index.

By considering inefficiencies, the productivity index in equation (9) can be divided into two parts, one calculating change in efficiency and the other calculating technical change, which is equivalent to a shift in the frontier technology.

$$\boldsymbol{M_i^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \frac{D_i^{t+1}(y^{t+1},x^{t+1})}{D_i^t(y^t,x^t)}\left[\frac{D_i^t(y^{t+1},x^{t+1})}{D_i^{t+1}(y^{t+1},x^{t+1})} \times \frac{D_i^t(y^t,x^t)}{D_i^{t+1}(y^t,x^t)}\right]^{1/2}} \quad \textbf{(9)}$$

In equation (9), the initial portion signifies the alteration in technical efficiency, while the latter part enclosed within the square root denotes the shift in technology. The shift in technical efficiency is determined by comparing the technical efficiency in period t+1 with that of period t. This essentially illustrates how the DMUs (PSCs) managed to approach the most efficient production frontier. A catch-up effect larger than 1, equal to 1, or fewer than 1 indicates an improvement, no change, or reduction from t to t+1, separately. The estimation of technical efficiency involves the multiplication of both scale efficiency and pure efficiency changes. Scale efficiency can be derived from any recorded measurements assuming either CRS or VRS. It is calculated as the ratio of CRS to VRS technical efficiency scores. Moreover, if the scale efficiency corresponds to 1, then the DMU is operating at an optimal scale. The distance function $\boldsymbol{D_i^t(y^t, x^t)}$ quantities the greatest possible reduction of x^t under the condition that $\boldsymbol{x^t/\lambda}$ is feasible.

We suggested technology at ***t*** by $\boldsymbol{S^t}$ and ***t+1*** by $\boldsymbol{S^{t+1}}$. The two observations $\boldsymbol{(x^t, y^t)}$ and $\boldsymbol{(x^{t+1}, y^{t+1})}$ are both feasible in their corresponding period. We can represent the productivity index in relation to the distance mentioned along the x-axis suggested in Figure 6 as follows:

$$\boldsymbol{M_i^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \frac{Ob/Oa}{Od/Oe}\left[\frac{Oa}{Oc} \times \frac{Of}{Oe}\right]^{1/2}} \quad \textbf{(10)}$$

Finally, based on two same scenarios but different approaches for CRS input-oriented MPI (suggested in Figure 7) the MPI is calculated as the Technical Change (TC) and Efficiency Change (EC):

$$\boldsymbol{MPI_{CRS}^t = TC(t) \times EC(t)} \quad \textbf{(11)}$$

This formula combines the two components to deliver an inclusive measure of productivity changes over time. MPI accounts for both changes in cost efficiency and overall efficiency in resource utilization, making it a valuable tool for evaluating productivity dynamics in healthcare applications.

While the basic MPI formula (TC × EC) is commonly used, the VRS formulation provides an additional level of detail by considering scale efficiency. This can be particularly useful in industries or systems where changes in scale play a significant role in productivity dynamics. In VRS, the outcome of the MPI can be demonstrated by multiplying the following elements of Pure Efficiency Change (PEC), TC, and Scale Efficiency Change (SEC).

$$\boldsymbol{PEC}=\frac{D_{t+1}^{\tau}(y^{t+1},x^{t+1})}{D_{t}^{\tau}(y^{t},x^{t})} \quad \textbf{(12)}$$

$$\boldsymbol{TC}=\left[\frac{D_{t}^{\tau}(y^{t},x^{t})}{D_{t+1}^{\tau}(y^{t},x^{t})}\times\frac{D_{t}^{\tau}(y^{t+1},x^{t+1})}{D_{t+1}^{\tau}(y^{t+1},x^{t+1})}\right]^{1/2} \quad \textbf{(13)}$$

$$\boldsymbol{SEC}=\left[\frac{SE_{t}(y^{t+1},x^{t+1})}{SE_{t}(y^{t},x^{t})}\times\frac{SE_{t+1}(y^{t+1},x^{t+1})}{SE_{t+1}(y^{t},x^{t})}\right]^{1/2} \quad \textbf{(14)}$$

$$\boldsymbol{M_{i}^{t+1}(y^{t+1},x^{t+1},y^{t},x^{t})=MPI_{VRS}^{t}=TC(t)\times PEC(t)\times SEC(t)} \quad \textbf{(15)}$$

The PEC factor evaluates whether the $\boldsymbol{DMU}$ under assessment has either approached or distanced from the frontier of the benchmark technology at time ***t+1*** while taking into consideration the benchmark technology at time $\boldsymbol{t}$. The TC factor signifies whether there has been a shift in the boundary of the technology over the given period. Additionally, the SEC factor assesses the impact of changes in the scale of $\boldsymbol{DMUs}$ on their productivity. As defined by the distance function, if the MPI or any of its constituent components falls below one, it indicates a regression; a value exceeding one denotes progress, and a value of one signifies a situation that has remained unchanged.

Consider $\boldsymbol{y_j^t=(y_{1j}^t,y_{2j}^t,\ldots,y_{mj}^t)}$ as outputs and $\boldsymbol{x_j^t=(x_{1j}^t,x_{2j}^t,\ldots,x_{nj}^t)}$ as inputs for PSC j (j=1,….,N) in period (t= t, t+1). So, distance function for the same period is as follows:

$$\boldsymbol{D_i^t(y^t,x^t)=\frac{1}{\theta_k^*}};\text{ where }\boldsymbol{\theta_k^*=max\theta} \quad \textbf{(16)}$$

We applied an input-oriented approach to assess the technical and scale efficiencies of PSCs, employing both the standard CRS) and VRS models. The input variables analyzed in this study are more flexible compared to the only one binary output (EVT performed or not).

3.3.6 Radial and Non-radial Data Envelopment Analysis Models

Envelopment DEA models can be referred to as radial efficiency quantities, as they improve all inputs or outputs of a DMU at a specific dimension. Fare and Lovell (114) proposed a non-radial measure that permits non-proportional reductions in positive inputs or enhancements in positive outputs. The following model summarizes the CRS non-radial input-oriented DEA model.

$$Z_0 = Min\theta - \left(\frac{1}{m}\sum_{i=1}^{m} \theta_i - \varepsilon\sum_{r=1}^{s} S_r^{+}\right) \quad (17)$$

$st.$

$\sum_{j=1}^{n} \lambda_j x_{ij} = \theta_i x_{i0} \qquad , i = 1,2,\dots,m;$

$\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^{+} = y_{r0} , r = 1,2,\dots,s;$

$\theta_i \leq 1 \qquad , i = 1,2,\dots,m;$

$\lambda_j \geq 0 \qquad , j = 1,2,\dots,n \quad , \varepsilon \geq 0$

By incorporating the $\sum_{j\neq 0}^{n} \lambda_j = 1$, into model (8), VRS is achieved. By incorporating the $\sum_{j\neq 0}^{n} \lambda_j \leq 1$ NIRS is achieved. By incorporating the $\sum_{j\neq 0}^{n} \lambda_j \geq 1$ NDRS) is achieved. Finally, the efficient targets are $\ddot{x_{i0}} = \theta_i^{*} x_{i0}$ and $\ddot{y_{r0}} = \theta_i^{*} x_{i0} = y_{r0} + S_r^{+*}$.

The slacks in the non-radial DEA models are improved in a second stage model where θ_i^{*} **or** $\varphi_r^{*}$are fixed. As an example, for output slacks in input-oriented non-radial under CRS we have:

$$Max \sum_{i=1}^{m} S_i^{-} \quad (18)$$

$st.$

$\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^{-} = x_{i0} \qquad , i = 1,2,\dots,m;$

$\sum_{j=1}^{n} \lambda_j y_{rj} = \varphi_r^{*} y_{r0} \qquad , r = 1,2,\dots,s;$

$\theta_i \leq 1 \qquad , i = 1,2,\dots,m;$

$\lambda_j \geq 0 \qquad , j = 1,2,\dots,n$

And in input slacks for output-oriented non-radial under CRS we have:

$$Max \sum_{r=1}^{s} S_r^{+} \quad (19)$$

$st.$

$\sum_{j=1}^{n} \lambda_j x_{ij} = \theta_i^{*} x_{i0} \qquad , i = 1,2,\dots,m;$

$\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^{+} = y_{r0} \qquad , r = 1,2,\dots,s;$

$\theta_i \leq 1 \qquad , i = 1,2,\dots,m;$

$\lambda_j \geq 0 \qquad , j = 1,2,\dots,n$

It should be noted that, in input-oriented non-radial DEA models, there are no input slacks, and in output-oriented non-radial DEA models, there are no output slacks.

Both non-radial and envelopment produce identical frontiers, but they can generate distinct efficient targets, even in cases where the envelopment models have no non-zero slacks. For example, if we change the second input of DMU6 in Figure 7, the input-oriented CRS envelopment model generates the efficient target of D with all nonzero slacks. Whereas the input-oriented CRS non-radial DEA model generates DMU2 as the efficient target for DMU6. It should be noted that both models generate the same target of DMU3 for DMU4. Figure 9 shows input-oriented radial and non-radial movements.

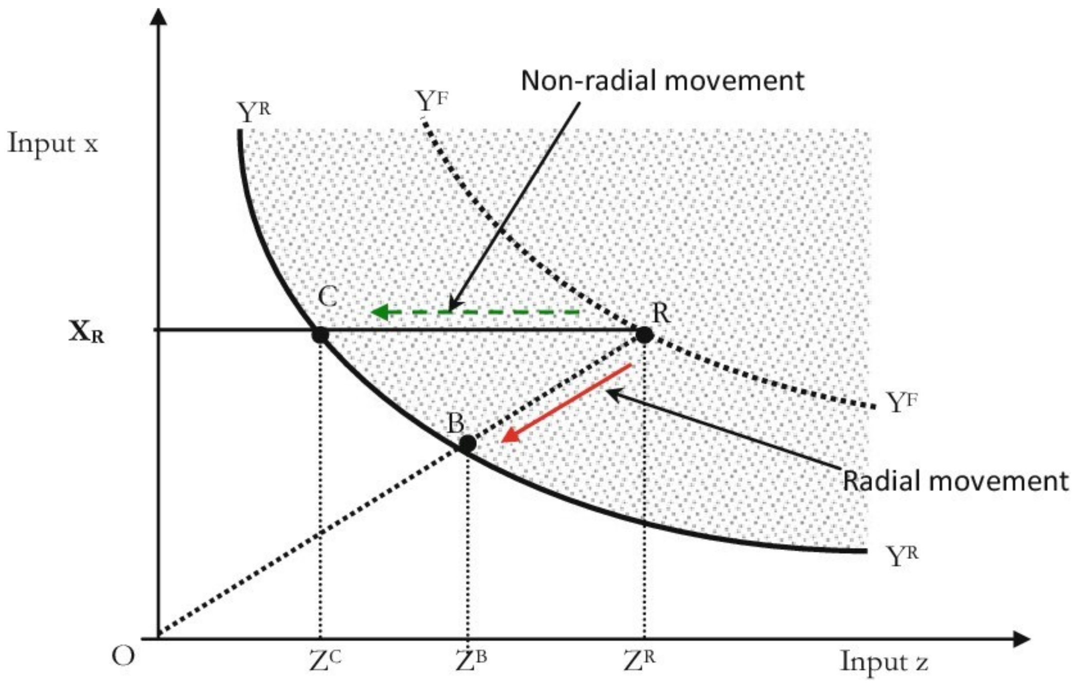

Figure 9: Input Oriented Radial and non-radial DEA.

3.3.7 Data Description

This section includes the following three subsections:

3.3.7.1 The Selected Data Attributes for Data Envelopment Analysis Assessment

In the context of DEA, the choice of inputs and outputs is a critical step. Table 4 shows a visible demonstration of these selections.

Table 4: The Selected Data Attributes for DEA Assessment.

No	Data Points
1	Age
2	Sex
3	ASPECTS
4	Clot/Occlusion Location
5	Collateral Status
6	Thrombolysis given
7	Onset to Arrival 1st Time
8	Onset to 1st CT
9	Arrival 1st to CSC Time/ Door-In-Door-In Time
10	Driving Distance
11	Euclidean Distance
12	EVT performed or not?

The dataset applied in this study encompasses a diverse array of demographic and clinical data, workflow times, and geographic distances pivotal for comprehensive assessment. It comprises information from 5156 patients of ischemic stroke patients, spanning from January 1, 2018, to December 31, 2021. Age, a fundamental demographic parameter, wields substantial influence over various facets of the medical treatment process. Sex (male vs female) is not considered as an input in the present context. The ASPECTS emerges as a pivotal tool in stroke evaluation, leveraging CT scans to discern early indicators of ischemic changes in the cerebral tissue. The precise localization of clots or occlusions within blood vessels, denoted as Clot/Occlusion Location, emerges as a pivotal determinant in shaping treatment strategies. Collateral status refers to the circulatory system's ability to create alternative routes for blood flow when a vessel is blocked, crucial for maintaining blood supply to tissues and organs and reducing the risk of ischemia. It is assessed in three categories: "good" indicates well-developed alternative vessels, offering effective bypass; "intermediate" suggests less developed routes, potentially less efficient in preventing ischemia; and "poor" signifies limited alternative routes, increasing the risk of early acute infarction. Evaluating collateral status is vital in cases of vascular blockages, influencing treatment decisions for conditions like coronary artery disease and stroke. Various imaging techniques, such as angiography, provide valuable insights into collateral circulation, aiding in treatment planning. Thrombolysis given input serves as a binary indicator denoting whether patients received thrombolysis treatment before being transferred for EVT. Workflow measures including Onset to Arrival 1st Time, quantifying the interval between symptom onset and the patient's arrival at the PSC, bear substantial relevance in gauging treatment timeliness. Likewise, Onset to 1st CT, delineating the duration between symptom onset and the start of the NCCT scan at the PSC, assumes paramount importance in expediting diagnosis and therapeutic initiation. Arrival 1st to CSC Time/Door-In-Door-In Time quantifies the elapsed time from the patient's initial arrival at the PSC to their subsequent arrival at the CSC, thus constituting a pivotal metric in evaluating the efficacy of the transfer process. The physical distance from the PSC via road to reach the CSC, encapsulated as Driving Distance for a ground ambulance, emerges as a logistical variable exerting a notable impact on treatment timelines. Furthermore, Euclidean Distance between the PSC and CSC denotes the linear spatial separation between pertinent locations, signifying the distance when a helicopter is used for transfer. From this array of variables, Age, ASPECTS, Collateral, thrombolysis given, Onset to Arrival 1st Time, Onset to 1st CT, Arrival 1st to CSC Time/Door-In-Door-In Time, Driving Distance, and Euclidean Distance have been judiciously selected as inputs for the ensuing DEA. Finally, an auxiliary variable serves to denote whether EVT was performed or not, providing the only output variable in this analytical framework.

The selected inputs (inputs 6 to 11 in Table 4), play a crucial role in the analysis. These inputs have been specifically identified for their direct influence on the process being evaluated. The key inputs with notable impacts, featuring both positive and negative effects on efficiency within our DEA model, encompass thrombolysis given, onset to arrival at PSC time, onset to the 1st CT time, Door-In-Door-In Time (arrival to PSC to arrival to CSC time), driving distance, and Euclidean distance. These inputs collectively capture crucial aspects of the evaluation, reflecting elements such as medical intervention, time intervals, and spatial considerations, thereby providing a comprehensive understanding of efficiency factors in the studied context. In our study, we conduct a comprehensive comparative analysis between two parts: one considers Age, ASPECTS, and Collateral inputs, while the other excludes them. This dual approach enables a nuanced exploration of the impact of these inputs on efficiency scores without delving into specific modeling techniques. The first part, encompassing all inputs, establishes a baseline understanding of efficiency outcomes influenced by Age, ASPECTS, and Collateral. In contrast, the second part focuses solely on time and distance-related inputs, aiming to minimize transfer time in stroke care. The results section details the comparative analysis, shedding light on the differential efficiency landscapes between these two parts and providing insights into the role of Age, ASPECTS, and Collateral in optimizing stroke care processes. However, it's important to note that certain variables, highlighted in blue, possess a different nature. These include Sex, and Clot/Occlusion Location. These variables are categorical, meaning they represent distinct categories or groups rather than continuous numerical values. In the case of Sex, it represents a binary classification (male or female), while Clot/Occlusion Location involves different possible categories. So, in DEA, including categorical variables as inputs can be problematic. DEA operates on numeric data and assumes a continuous, numerical nature of inputs and outputs. Categorical variables do not conform to this assumption. For instance, how do you quantify 'male' or 'female' in a way that can be used mathematically in the DEA model? Furthermore, including categorical variables in DEA may lead to misinterpretation or erroneous results. The model may not effectively differentiate between categories or may produce outputs that are difficult to interpret or utilize in a meaningful way. Therefore, in the case of Sex, and Clot/Occlusion Location, it is considered unnecessary to include them as inputs in DEA due to their categorical nature. Instead, these variables may be more appropriately used for descriptive or stratified analyses, providing additional context to the results obtained from the DEA model. Additionally, it's important to acknowledge our single highlighted green variable as the output in the DEA model, which is a crucial component in assessing the efficiency of the evaluated process. This output variable has been carefully selected for its relevance and significance in measuring the effectiveness of stroke treatment. In the context of data normalization, 'Min-Max Scaling' or 'Min-Max Normalization' is employed to rescale variables to a range between 0 and 1. Among the variables mentioned, ASPECTS and Collateral are considered benefits, while Age, Onset to Arrival 1st Time, Onset to 1st CT Arrival, Arrival 1st to CSC Time/ Door-In-Door-In Time, Driving Distance, and Euclidean Distance are viewed as costs in the normalization process. This technique ensures that all variables operate within a consistent scale, which is crucial for various types of analyses and modeling, while preserving the underlying relationships between the variables.

3.3.7.2 Driving Distance and Euclidean Distance

Driving distance refers to the actual length of the path one would need to travel by road from one location to another, factoring in the layout of roads, highways, streets, as well as any necessary detours or turns. This metric is crucial for providing the distance when a ground ambulance is used to transfer the patient from the PSC to CSC. On the other hand, Euclidean distance measures the straight-line distance between two points in space, derived from the Pythagorean theorem., it provides a straightforward measure of spatial separation, and it provides the distance when a helicopter is used to transport the patient from the PSC to the CSC. The distances, including both driving distance and Euclidean distance, were assessed from the Nova Scotia referring medical centers to the EVT center. These computations were executed using Google Maps for each of the 10 referring center locations. The detailed outcomes are described in Table 5 for your reference.

Table 5: The Driving Distance and Euclidian Distance Between each Primary Stroke Centre and Comprehensive Stroke Centre.

PSCs	Driving Distance (km)	Euclidian Distance (km)
1	157	127.57
2	101	79.1
3	92.7	81.5
4	195	137
5	359	250.23
6	217	166.9
7	302	221.7
8	8	3.28
9	105	87.4
10	400	312.58

Eight PSCs with a small number of patients were combined into four DMUs, each comprising two PSCs. These merged PSCs not only serve a small patient population, but they are also located near each other geographically (In Table 5. PSCs included in DMU1 are PSCs numbered 5 and 10, PSCs included in DMU2 are PSCs numbered 3 and 4, PSCs included in DMU3 are PSCs numbered 1 and 6, PSCs included in DMU4 are PSCs numbered 2 and 7). Two PSCs numbered 8 and 9 were maintained as separate entities due to their substantial patient volume. Table 3 shows the suggested division.

Table 6: PSCs and DMUs in the Second Scenario.

PSCs	DMUs
5 and 10	1
3 and 4	2
1 and 6	3
2 and 7	4
8	5
9	6

3.3.7.3 Data Sources: Provincial Registry and Manually Imaging

Nova Scotia has a provincial stroke registry that includes all stroke patients that were admitted to a hospital in the province. It includes key demographic, clinical, process, and outcome measures for each stroke patient. This registry was used to identify patients that were transferred. The dataset encompasses records from 5156 cases of ischemic stroke patients, spanning the period from January 1, 2018, to December 31, 2021, with a specific focus on individuals sourced exclusively from 10 designated PSCs. Out of this group, 3102 patients were received at these centers, marking a significant subset of the total population. It is imperative to note that our research exclusively concentrated on patient transfers originating from Patient Service Centers, culminating at the CSC, underscoring the specificity of our investigation. Within this context, only 238 patients out of the 3102 were ultimately transferred to the CSC, representing those deemed in need of higher-level care, which reasonably suggests an inclination towards EVT interventions. However, it is worth mentioning that 10 patients were excluded from the study due to discrepancies in their Health Card Numbers (HCN), resulting in an inability to locate their data. Consequently, the final analysis was conducted on a group of 115 patients, ensuring a rigorous and accurate examination.

The suggested data was obtained from the provincial stroke registry: age, PSC hospital, onset time, time of arrival at PSC, time of departure from PSC, and time of arrival at CSC. From this data the following data was calculated: driving distance, Euclidean distance, onset to arrival at PSC, onset to 1st CT, arrival at PSC to arrival at CSC.

The imaging data and whether EVT procedure was done was then manually collected. Using the HCN for each identified patient, the NCCT image was read for the ASPECTS and collateral status. Similarly, imaging data was used to find the EVT procedure to determine if EVT was performed. Figure 10 illustrates the process of filtering EVT-eligible patients in four distinct steps.

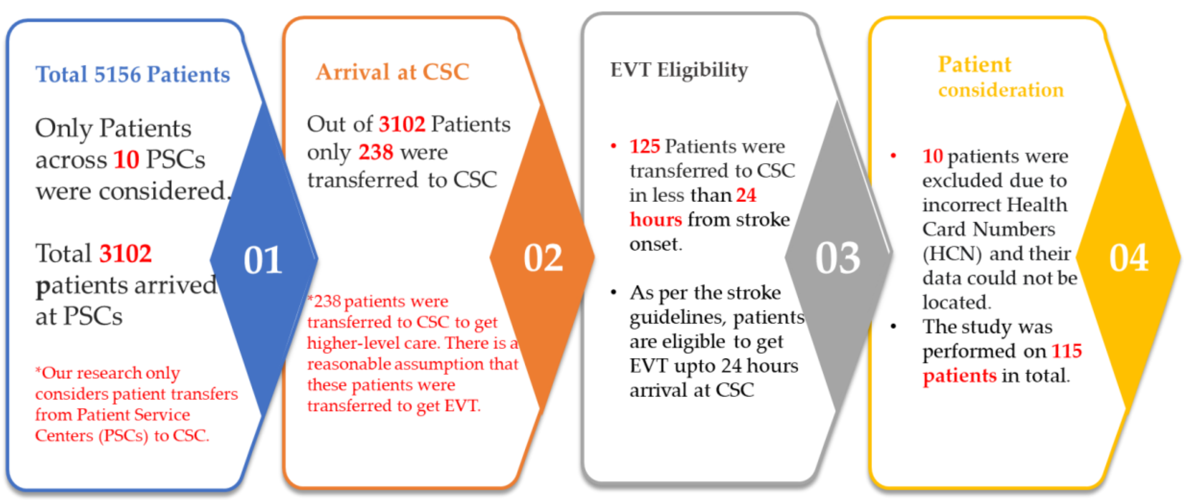

Figure 10: Four Steps of Filtering for Endovascular Thrombectomy Eligible Patients in the Provincial Registry.

3.4 Results, and Final Evaluation of Decision-Making Units

This study aims to improve stroke care for rural populations by analyzing nine inputs, such as age and distance between PSCs and CSC that administered EVT treatment. The only output variable is: whether EVT is conducted or not. To protect confidentiality and privacy, the names of the province and primary stroke center have not been disclosed. In the subsequent sections, we will provide more comprehensive information for both the first and second subsections.

3.4.1 First Scenario

In the initial stage, 115 patients were regarded as distinct DMUs to assess ten PSCs. This assessment applied an input-oriented VRS approach, assisted by super efficiency using the PyDEA tool, which is recognized for its versatility in managing DMUs, inputs, and outputs without constraints. In this section, as we have 115 patients or DMUs, there is no need to consolidate PSCs as was done in the second scenario. In the second scenario, eight PSCs with limited patient counts were combined into four DMUs, each composed of two PSCs. Therefore, in this section, we consider all ten PSCs. Table 4 presents the details of the 115 patients and their corresponding attended PSCs. It's worth mentioning that the numbering (1 to 10) corresponds to the suggestions provided in Table 7 for the PSCs.

Table 7: The Suggested Final 115 Patients or DMUs and Their Attended PSCs.

DMUs	PSCs	DMUs	PSCs	DMUs	PSCs	DMUs	PSCs	DMUs	PSCs
1	2	24	8	47	10	70	1	93	1
2	6	25	8	48	9	71	8	94	9
3	7	26	9	49	10	72	8	95	8
4	2	27	6	50	7	73	8	96	3
5	5	28	10	51	1	74	9	97	2
6	7	29	8	52	8	75	1	98	6
7	2	30	8	53	3	76	8	99	9
8	8	31	7	54	7	77	8	100	3
9	3	32	3	55	4	78	8	101	9
10	10	33	10	56	3	79	10	102	9
11	8	34	8	57	9	80	7	103	9
12	9	35	8	58	9	81	1	104	9
13	2	36	5	59	1	82	7	105	9
14	8	37	8	60	5	83	7	106	3
15	2	38	2	61	10	84	9	107	9
16	8	39	7	62	9	85	8	108	9
17	8	40	2	63	3	86	8	109	2
18	8	41	8	64	8	87	8	110	6
19	8	42	9	65	9	88	6	111	9
20	8	43	10	66	2	89	10	112	4
21	8	44	6	67	7	90	8	113	2
22	8	45	3	68	9	91	8	114	2
23	8	46	2	69	3	92	5	115	7

Table 8 shows efficiency results for 115 patients in VRS input-oriented model.

Table 8: Efficiency Results for 115 Patients in VRS Input Oriented Model Including All Inputs.

DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency
1	1	24	1	47	1	70	0.8	93	1
2	0.89106315	25	1	48	0.90531194	71	1	94	1
3	1	26	1	49	1	72	1	95	1
4	0.99540257	27	1	50	1	73	1	96	1
5	1	28	1	51	1	74	0.80897522	97	1
6	0.8	29	1	52	1	75	1	98	1
7	0.90819778	30	1	53	0.9901267	76	1	99	1
8	1	31	0.90586991	54	1	77	1	100	1
9	1	32	0.70541343	55	1	78	1	101	0.9612301
10	1	33	1	56	1	79	1	102	1
11	1	34	1	57	1	80	1	103	1
12	0.88097027	35	1	58	1	81	1	104	1
13	0.90417857	36	1	59	1	82	1	105	1
14	1	37	1	60	1	83	1	106	1
15	1	38	0.88484381	61	1	84	1	107	0.86256741
16	1	39	1	62	1	85	1	108	1
17	1	40	1	63	0.9	86	1	109	1
18	1	41	1	64	1	87	1	110	1
19	1	42	1	65	1	88	1	111	1
20	1	43	1	66	1	89	1	112	1
21	1	44	1	67	0.5368217	90	1	113	1
22	1	45	1	68	1	91	1	114	1
23	1	46	1	69	0.8	92	1	115	1

In this part, our focus shifts to a detailed examination of the outcomes derived from the two distinct parts of our analysis—one that includes Age, ASPECTS, and Collateral inputs that exclude them. So, in the first part, where all inputs are considered, the analysis reveals a distribution of efficiency scores among DMUs. Notably, the inclusion of Age, ASPECTS, and Collateral introduces variability in the efficiency landscape, emphasizing the impact of neurological and collateral status on overall efficiency. The baseline understanding derived from this part forms a crucial reference point for evaluating the effectiveness of stroke care processes when accounting for these specific inputs. Based on Table 8, 98 patients are considered efficient, and 17 patients received efficiency scores below 1. Table 9 shows the super-efficiency of the first part.

Table 9: Super Efficiency Results for 115 Patients in VRS Input Oriented Model Including All Inputs.

DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency
1	1	24	1.2208191	47	1.2942053	70	0.8	93	1.0025925
2	0.89106315	25	1	48	0.90531194	71	1	94	1
3	1	26	1.2885566	49	1	72	1.2166742	95	1
4	0.99540257	27	1	50	1	73	1.5932243	96	1
5	1	28	1	51	1	74	0.80897522	97	1
6	0.8	29	1	52	1.3880813	75	1.3863572	98	1
7	0.90819778	30	1	53	0.9901267	76	1.0137769	99	1.0171683
8	1.6156897	31	0.90586991	54	1.1252411	77	1.1417537	100	1
9	1	32	0.70541343	55	1.0543576	78	1	101	0.9612301
10	1	33	1	56	1	79	1.3835616	102	1
11	1	34	1.4204012	57	1.2009917	80	1.630363	103	1
12	0.88097027	35	1.4900112	58	1	81	1.4814815	104	1.8571432
13	0.90417857	36	1	59	1	82	1	105	1
14	1	37	1	60	1	83	1.7792685	106	1.0492335
15	1	38	0.88484381	61	1	84	1.1460134	107	0.86256741
16	1.0326639	39	1	62	1.1231954	85	1.006602	108	1.0400273
17	1	40	1	63	0.9	86	3.7112112	109	1.1054744
18	4.92055	41	1.306763	64	1.018913	87	1.1634706	110	1
19	1	42	1.0971618	65	1.0639581	88	1	111	1.0185501
20	1.7	43	1	66	1.1103448	89	1.3644427	112	1
21	1	44	1	67	0.5368217	90	1.0348789	113	1
22	5.3997535	45	1.303289	68	1.0790837	91	1	114	1
23	1.0261391	46	1	69	0.8	92	1	115	1.0569433

In contrast, the second part strategically excludes Age, ASPECTS, and Collateral, homing in on inputs directly associated with time and distance. This refined focus aligns with our primary objective of minimizing transfer time and futile transfers in stroke care. By concentrating on aspects such as onset to Arrival at PSC time, onset to 1st CT time, arrival to PSC to arrival to CSC time (Door-In-Door-In Time), and distance metrics like Driving Distance and Euclidean Distance, this part aims to discern the efficiency landscape under conditions directly relevant to our study's overarching goal.

The resulting efficiency scores from this second part offer a distinct perspective, showcasing the impact of excluding Age, ASPECTS, and Collateral on overall efficiency outcomes. This comparison allows us to pinpoint how the refined set of time and distance-related inputs contributes to optimizing stroke care processes, offering insights into potential improvements.

In Table 8, findings reveal that many efficient DMUs are indicative of potential inefficiencies. The key contributor to the prevalence of efficient DMUs appears to be the consideration of factors such as "Collateral" and "ASPECTS." The suggestion to remove these inputs implies that doing so would likely result in a greater number of inefficient DMUs. This strategic removal is proposed to enable decision-makers to pinpoint and address the primary reasons for inefficiency, thereby facilitating a more focused and targeted approach to improving overall decision-making processes.As we delve into the specific implications of including or excluding Age, ASPECTS, and Collateral, our analysis becomes a cornerstone for drawing meaningful conclusions. The detailed exploration of these comparative parts forms the bedrock for discussions on the optimal input configuration, informing decisions aimed at minimizing transfer time and optimizing the efficiency of stroke care processes. Table 10 shows efficiency for the second part of the study.

Table 10: Efficiency Results for 115 Patients in VRS Input Oriented Model Excluding Suggested Inputs.

DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency
1	0.37047866	24	1	47	0.80579527	70	0.43720876	93	0.52152339
2	0.53481983	25	1	48	0.74147996	71	1	94	0.68987501
3	0.56055283	26	1	49	0.14632709	72	1	95	1
4	0.99369193	27	0.3276777	50	0.5620658	73	1	96	0.82003173
5	0.44884999	28	0.66201662	51	0.36096889	74	0.20402824	97	0.70745959
6	0.49159373	29	1	52	1	75	1	98	0.47513516
7	0.73559787	30	1	53	0.80681012	76	1	99	0.86820806
8	1	31	0.84328033	54	0.17512331	77	1	100	0.25199846
9	0.70605276	32	0.41663489	55	0.84850463	78	1	101	0.87979115
10	0.20650682	33	0.20650682	56	0.62796032	79	0.43702871	102	0.68117598
11	1	34	1	57	0.99443054	80	1	103	0.47440186
12	0.87392301	35	1	58	0.57679494	81	0.57771623	104	1
13	0.52225037	36	0.40122734	59	0.71707895	82	0.50320452	105	0.56621046
14	1	37	1	60	0.45543838	83	1	106	0.74787362
15	0.27492907	38	0.59335672	61	0.20353869	84	1	107	0.58849399
16	1	39	0.39803553	62	0.50110212	85	1	108	0.81726094
17	1	40	0.87347816	63	0.63495079	86	1	109	1
18	1	41	1	64	1	87	1	110	0.59255174
19	1	42	1	65	0.90015285	88	0.42847891	111	0.81142452
20	1	43	0.40999737	66	1	89	0.62129719	112	0.36103124
21	1	44	0.59054233	67	0.38917901	90	1	113	0.17612853
22	1	45	1	68	0.1770921	91	1	114	0.63121715
23	1	46	0.61392984	69	0.23178621	92	0.35788511	115	0.374154

Based on Table 10, 43 patients are considered efficient because they achieved an efficiency score of 1. This means they are using their resources optimally to achieve their outcomes. So, 72 patients received efficiency scores below 1, indicating that they are not using their resources optimally to achieve their outcomes. They may have room for improvement in their resource allocation or utilization. Table 11 shows super efficiency for the second part of the study.

Table 11: Super Efficiency Results for 115 Patients in VRS Input Oriented Model Excluding Suggested Inputs.

DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency	DMUs	Efficiency
1	0.37047866	24	1	47	0.80579527	70	0.43720876	93	0.52152339
2	0.53481983	25	1	48	0.74147996	71	1	94	0.68987501
3	0.56055283	26	1.1322636	49	0.14632709	72	1	95	1
4	0.99369193	27	0.3276777	50	0.5620658	73	1	96	0.82003173
5	0.44884999	28	0.66201662	51	0.36096889	74	0.20402824	97	0.70745959
6	0.49159373	29	1	52	1	75	1	98	0.47513516
7	0.73559787	30	1	53	0.80681012	76	1	99	0.86820806
8	1	31	0.84328033	54	0.17512331	77	1	100	0.25199846
9	0.70605276	32	0.41663489	55	0.84850463	78	1	101	0.87979115
10	0.20650682	33	0.20650682	56	0.62796032	79	0.43702871	102	0.68117598
11	1	34	1	57	0.99443054	80	1.5294118	103	0.47440186
12	0.87392301	35	1	58	0.57679494	81	0.57771623	104	1.8571432
13	0.52225037	36	0.40122734	59	0.71707895	82	0.50320452	105	0.56621046
14	1	37	1	60	0.45543838	83	1.2086956	106	0.74787362
15	0.27492907	38	0.59335672	61	0.20353869	84	1.0827967	107	0.58849399
16	1	39	0.39803553	62	0.50110212	85	1	108	0.81726094
17	1	40	0.87347816	63	0.63495079	86	3.7112112	109	1.0958577
18	4.92055	41	1.306763	64	1	87	1	110	0.59255174
19	1	42	1	65	0.90015285	88	0.42847891	111	0.81142452
20	1.7	43	0.40999737	66	1	89	0.62129719	112	0.36103124
21	1	44	0.59054233	67	0.38917901	90	1	113	0.17612853
22	5.3997535	45	1.2853258	68	0.1770921	91	1	114	0.63121715
23	1	46	0.61392984	69	0.23178621	92	0.35788511	115	0.374154

The consistent score of 1 implies that these DMUs have maximally harnessed their available resources, leading to optimal and highly effective outcomes. Essentially, they are operating at the zenith of efficiency, leaving little to no room for further improvement based on the criteria outlined in the DEA model.

This observation suggests that the identified DMUs have successfully utilized their inputs to generate the desired outputs in an exceptionally effective manner. Their performance is not only efficient but has surpassed the benchmark set by the DEA model, indicating a high level of productivity and resource utilization. Consequently, these DMUs can be considered exemplars in terms of operational efficiency within the analyzed context, showcasing a remarkable ability to achieve optimal results with the given resources and constraints.

Radial DEA and non-radial DEA represent two distinct approaches to measuring efficiency within this framework. Radial DEA determines efficiency scores based on the distance of each DMU from the efficient frontier, a hyperplane enveloping all DMUs, with the assumption that any deviation from this frontier signifies inefficiency. The radial measure of efficiency is derived from the ratio of a DMU's output/input vector to a weighted average of these vectors for the efficient units. It focuses on scale inefficiency and is based on the premise that efficiency improvements involve moving closer to the efficient frontier. Non-radial DEA, on the other hand, introduces a more nuanced perspective by considering both radial and non-radial components of inefficiency. Unlike radial DEA, non-radial DEA allows for deviations in both input and output directions from the efficient frontier, providing a more comprehensive analysis. It breaks down inefficiency into two components: radial inefficiency, associated with distance from the efficient frontier, and non-radial inefficiency, associated with the direction of deviation. This approach enables a more refined understanding of inefficiency by accounting for both scale inefficiency and allocative inefficiency. The choice between radial and non-radial DEA depends on the specific characteristics of the decision-making problem, the nature of the available data, and the nuances of the efficiency evaluation being conducted.

Based on suggested data in Table 7 and 10, Table 12 provides an evaluation of DEA targets, including original values, target values, and the corresponding differences for both radial and non-radial categories for the first DMU in PSC 2.

Table 12: Original Values, Target Values, Radial, and Non-radial for the Second DMU in the First Scenario.

Category	Original	Target	Radial	Non-radial
DIDI Time (Door-In-Door-In)	0.807957154	0.147523055	-0.50862627	-0.151807829
Driving Distance	0.3925	0.145412874	-0.247087126	0
Euclidean Distance	0.408119521	0.149670629	-0.256919948	-0.001528944
Onset_to_1st_CT	0.101744186	0.03769405	-0.064050136	0
Onset_To_Arrival_1st	0.15942029	0.048331173	-0.100358475	-0.010730642

The presented values represent the efficiency scores and corresponding differences for five key inputs that warrant special attention. These values are crucial in identifying areas for improvement and optimizing the performance of inefficient units to enhance their efficiency and effectiveness.

The original value for "Onset to Arrival 1st" is 0.15942029, and the target value after the DEA analysis is 0.048331173. The radial difference, which represents the degree of improvement achievable without altering the input mix, is -0.100358475. The non-radial difference, indicating the portion of improvement that involves adjusting input levels, is -0.010730642. For "Onset To 1st CT," the original value is 0.101744186, and the target value post-DEA analysis is 0.03769405. The radial difference is -0.064050136, denoting potential improvement without changing input proportions. The non-radial difference is -0, indicating no improvement required involving input level adjustments. A negative radial difference suggests potential for improvement, while a zero non-radial difference indicates that the input levels are already considered optimal. Combining these, implies that adjustments can be made to inputs and outputs to move the system toward greater efficiency. The original "Euclidean Distance" value is 0.408119521, while the target value is 0.149670629 following DEA evaluation. The radial difference is -0.256919948, suggesting potential enhancement without altering input mix. The non-radial difference is -0.001528944, implying minimal improvement involving input level adjustments. DIDI Time" initially measures 0.807957154, and after DEA analysis, the target value is 0.147523055. The radial difference is -0.50862627, indicating potential improvement without changing input proportions. The non-radial difference is -0.151807829, suggesting minimal improvement involving input level adjustments. The original value for "Driving Distance" is 0.3925, and the target value post-DEA analysis is 0.145412874. The radial difference is -0.247087126, representing potential improvement without changing input proportions. The non-radial difference is 0. When the non-radial difference, indicating the portion of improvement related to adjusting input levels, is 0, it generally means that there is no need for adjustment or optimization in the input levels. In the context of DEA efficiency analysis or performance measurement, a non-radial difference of 0 implies that the current input levels are already considered optimal, and no further improvement can be achieved by altering the input mix. In simpler terms, if the non-radial difference is 0, the system or process is already operating at its most efficient point concerning the input levels being considered. There is no room for improvement by adjusting these inputs further.

Appendix B (Table 29) delineates the suggested evaluations for all 115 patients, or DMUs. The section provides a thorough exploration of assessments and recommendations, offering a comprehensive overview of the proposed evaluations for each individual.

Appendix B (Table 30) adheres to a uniform methodology, extending the same approach to super-efficiency for all 115 patients, or DMUs. The content within this section reflects the application of a standardized process, specifically tailored for evaluating and achieving super-efficiency.

Based on the data presented in Tables 7, 10, and 11 we have conducted a ranking of all ten PSCs by evaluating the average technical efficiency of patients who sought services at each respective PSC in Table 13. This analysis allows us to assess the effectiveness and performance of these centers in delivering care to their respective patient populations.

This ranking is based on the calculated efficiency scores for each PSC. PSC 8 has achieved the highest efficiency score of 1, indicating optimal performance. PSC 10, on the other hand, has the lowest efficiency score at 0.41100162.

Table 13: Ranking of Ten Primary Stroke Centres by Evaluating the Average Technical Efficiency of Attended Patients.

PSCs	Ranking	Ave. Efficiency Score
1	6	0.602416037
2	3	0.653270607
3	4	0.62440989
4	5	0.604767935
5	9	0.415850205
6	8	0.491534278
7	7	0.572471733
8	1	1
9	2	0.730754559
10	10	0.41100162

The significance of the distance between PSCs and CSC is evident in contrasting scenarios. PSC 8, the nearest to the CSC, attains the highest efficiency score, suggesting that spatial proximity positively impacts operational efficiency. The reduced distance likely facilitates quicker responses and seamless collaboration. In contrast, PSC 10, situated farthest from the CSC, receives the lowest efficiency score, indicating that increased distance hampers operational efficiency. Longer distances may lead to delays and logistical challenges, impacting the timely delivery of stroke care. These results underscore the crucial role of geographical factors in shaping the efficiency of stroke care networks, emphasizing the need for strategic planning to minimize distances between primary and comprehensive stroke centers for improved overall system performance.

It's important to further analyze the factors contributing to these scores to identify areas for improvement and potential best practices to be shared across the centers. In DEA, the terms "Reference Set," "Peer Weight," and "Peer Count" are key concepts used to evaluate the relative efficiency of DMUs in a dataset. Here's what they mean:

Reference Set: The reference set refers to a cluster of DMUs against which the efficiency of a specific DMU is evaluated. These DMUs serve as benchmarks or reference points. The efficiency of the DMU being evaluated is assessed in relation to its ability to perform as well as, or better than, the units in the reference set. The goal is to identify the most efficient units that can potentially serve as benchmarks for less efficient ones.

Peer Weight: Peer weights are coefficients assigned to each DMU in the reference set. These weights are determined by the DEA model and represent the relative worth or influence of each benchmark unit in the evaluation of the DMU being assessed. The weights are used to aggregate the performance measures of the reference set in a way that reflects the efficiency of the DMU under assessment.

Peer Count: Peer count refers to the number of DMUs contained in the reference set. It represents the size of the benchmark group used to evaluate the efficiency of a specific DMU. The choice of peer count can have an impact on the results of the DEA analysis, and it is an important parameter to consider when conducting the evaluation.'

Due to the large number of 72 inefficient patients in the initial scenario, it is impractical to include evaluations for each patient in this paper. As a result, we have chosen to focus on the five patients with various efficiency scores for detailed analysis. This approach allows us to provide a representative overview of the inefficiencies observed within this group, while also managing the scope of the study for clarity and conciseness. Table 14 shows reference set, peer weight, peer count, classification, and super-rank.

Table 14. Reference Set, Peer Weight, Peer Count, and Classification of Three Selected Patients or DMUs Among 115 Patients.

DMUs	PSCs	Efficiency	Reference Set (Efficient DMUs Number)	Peer Weight (Lambdas)	Peer Count	Classification	Super-Rank
1	2	0.37047866	42,41,18	0.51716649,0.11235486,0.37047866	-	IRS	70
2	6	0.53481983	26,104,109,22	0.25333833,0.13750643,0.42725536,0.18189988	-	IRS	51
26	9	1.1322636	84,45,86	0.79086679,0.13440915, 0.074724063	36	CRS	10

The efficiency score for patient (DMU) number 1 who attended PSC number 2 is 0.37047866. This score indicates that, according to the DEA analysis, patient 1 is operating at approximately 37.04% of the maximum possible efficiency given the inputs and outputs considered in the analysis. In other words, there is potential for improvement in how resources are utilized. Reference sets 42, 41, and 18 are the specific patient numbers selected as benchmarks or reference points to evaluate the efficiency of patient number 1. Patients 42, 41, and 18 are considered comparable to patient 26 in terms of their inputs and outputs. These patients serve as reference points to assess patient 1's performance. The peer count represents the number of reference units included in the evaluation. In this case, since the suggested DMU is not efficient, it cannot be peer counted. Peer weight or lambda are the weights assigned to each of the reference patients (42, 41, and 18) in the DEA model. These weights indicate the relative importance or contribution of each benchmark patient in the evaluation of patient 1's efficiency. The lambda values suggest that patient 42 has the highest relative importance (0.51716649). The IRS classification indicates the nature of input-oriented DEA model. Lastly, the super efficiency rank of 70 indicates where patient 1 stands among the 115 patients in the analysis.

The efficiency score for patient number 2 who attended PSC number 6 among the 115 patients is 0.53481983. This score suggests that, based on the DEA, patient 2 is operating at approximately 53.48% of the maximum achievable efficiency given the specific inputs and outputs considered in the analysis. This indicates that there is some room for improvement in how resources are utilized by patient 2. The reference sets, consisting of patients 26, 104, 109, and 22, are specific individuals chosen as benchmarks or reference points to evaluate patient 2's efficiency. These patients are deemed comparable to patient 2 in terms of their inputs and outputs, serving as reference points to gauge patient 2's performance. The peer count, in this case, is five, representing the number of reference units included in the evaluation. This means that four patients (26, 104, 109, and 22) are part of the reference set used to compare against patient 2. The lambdas, representing peer weights, are values assigned to each of the reference patients. These weights indicate the relative importance or contribution of each benchmark patient in the evaluation of patient 1's efficiency. For example, patient 109 has the highest relative importance with a lambda of 0.42725536. The classification of IRS indicates the nature of the DEA model used, focusing on optimizing the utilization of inputs to achieve higher levels of output, assuming the technology or production process is not perfectly scalable. Lastly, the super efficiency rank of 51 signifies where patient 2 stands among the 115 patients in the analysis when considering super efficiency.

The last selected DMU, representing an efficient patient in a healthcare context, demonstrates exceptional performance with an efficiency score of 1.1322636. This patient is assessed against a reference set of 36 DMUs, which includes both inefficient and efficient cases. This gives a relatively large set for benchmarking and evaluating the patient's efficiency. The peer weights, represented by lambdas, indicate the influence of each peer in determining the efficiency of the selected patient. The value of 1.1322636 suggests that these peer weights play a significant role in the efficiency calculation.

Appendix B (Table 31) outlines the recommended evaluations for all 115 patients, or DMUs. The content of this section offers insights into assessments and recommendations about each individual, providing a comprehensive overview of the suggested evaluations.

Appendix B (Table 32), a uniform approach is employed, maintaining consistency, particularly in the realm of super efficiency for all 115 patients, or DMUs. The document reflects the application of this standardized methodology throughout its content.

Before applying super-efficiency Table 15 shows ranking of DMUs for 115 patients in VRS input-oriented model.

Table 15: Ranking of DMUs for 115 Patients in VRS Input Oriented Model.

DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score
8	1	1	64	1	1	101	47	0.87979115	89	70	0.62129719	88	93	0.42847891
11	1	1	66	1	1	12	48	0.87392301	46	71	0.61392984	32	94	0.41663489
14	1	1	71	1	1	40	49	0.87347816	38	72	0.59335672	43	95	0.40999737
16	1	1	72	1	1	99	50	0.86820806	110	73	0.59255174	36	96	0.40122734
17	1	1	73	1	1	55	51	0.84850463	44	74	0.59054233	39	97	0.39803553
18	1	1	75	1	1	31	52	0.84328033	107	75	0.58849399	67	98	0.38917901
19	1	1	76	1	1	96	53	0.82003173	81	76	0.57771623	115	99	0.374154
20	1	1	77	1	1	108	54	0.81726094	58	77	0.57679494	1	100	0.37047866
21	1	1	78	1	1	111	55	0.81142452	105	78	0.56621046	112	101	0.36103124
22	1	1	80	1	1	53	56	0.80681012	50	79	0.5620658	51	102	0.36096889
23	1	1	83	1	1	47	57	0.80579527	3	80	0.56055283	92	103	0.35788511
24	1	1	84	1	1	106	58	0.74787362	2	81	0.53481983	27	104	0.3276777
25	1	1	85	1	1	48	59	0.74147996	13	82	0.52225037	15	105	0.27492907
26	1	1	86	1	1	7	60	0.73559787	93	83	0.52152339	100	106	0.25199846
29	1	1	87	1	1	59	61	0.71707895	82	84	0.50320452	69	107	0.23178621
30	1	1	90	1	1	97	62	0.70745959	62	85	0.50110212	10	108	0.20650682
34	1	1	91	1	1	9	63	0.70605276	6	86	0.49159373	33	109	0.20650682
35	1	1	95	1	1	94	64	0.68987501	98	87	0.47513516	74	110	0.20402824
37	1	1	104	1	1	102	65	0.68117598	103	88	0.47440186	61	111	0.20353869
41	1	1	109	1	1	28	66	0.66201662	60	89	0.45543838	68	112	0.1770921
42	1	1	57	44	0.99443054	63	67	0.63495079	5	90	0.44884999	113	113	0.17612853
45	1	1	4	45	0.99369193	114	68	0.63121715	70	91	0.43720876	54	114	0.17512331
52	1	1	65	46	0.90015285	56	69	0.62796032	79	92	0.43702871	49	115	0.14632709

With 43 patients already identified as efficient based on their initial assessment, the objective now is to further distinguish and rank these efficient units using a method called super efficiency analysis. This specialized technique allows for a more nuanced evaluation of their performance relative to each other. By applying super efficiency, we aim to uncover subtle differences in how these patients utilize their resources and achieve outcomes, ultimately providing a more detailed understanding of their relative effectiveness within the group of already efficient units. This additional level of analysis can offer valuable insights into potential areas of excellence or opportunities for improvement among these high-performing patients.

Table 16 displays the ranking of 43 super-efficient DMUs. When we apply super efficiency to 53 efficient DMUs with a score of 1, and then find that most of them still receive a score of 1, it means that these 30 DMUs are performing at the highest level of efficiency possible given the inputs and outputs considered in the analysis. This could indicate that these DMUs have effectively utilized their resources and achieved optimal outcomes. In other words, they are already operating at the peak of efficiency and there is no room for further improvement based on the specified inputs and outputs in the DEA.

Table 16: Ranking of Super-efficient DMUs with 43 Efficient Patients.

DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score
22	1	5.3997535	84	12	1.0827967	29	13	1	73	13	1
18	2	4.92055	8	13	1	30	13	1	75	13	1
86	3	3.7112112	11	13	1	34	13	1	76	13	1
104	4	1.8571432	14	13	1	35	13	1	77	13	1
20	5	1.7	16	13	1	37	13	1	78	13	1
80	6	1.5294118	17	13	1	42	13	1	85	13	1
41	7	1.306763	19	13	1	52	13	1	87	13	1
45	8	1.2853258	21	13	1	64	13	1	90	13	1
83	9	1.2086956	23	13	1	66	13	1	91	13	1
26	10	1.1322636	24	13	1	71	13	1	95	13	1
109	11	1.0958577	25	13	1	72	13	1			

Table 17 shows ranking of all 115 DMUs after applying super efficiency.

Table 17: Ranking of all 115 DMUs After Applying Super-efficiency.

DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score	DMUs	Ranking	Efficiency score
22	1	5.3997535	30	13	1	101	47	0.87979115	89	70	0.62129719	88	93	0.42847891
18	2	4.92055	34	13	1	12	48	0.87392301	46	71	0.61392984	32	94	0.41663489
86	3	3.7112112	35	13	1	40	49	0.87347816	38	72	0.59335672	43	95	0.40999737
104	4	1.8571432	37	13	1	99	50	0.86820806	110	73	0.59255174	36	96	0.40122734
20	5	1.7	42	13	1	55	51	0.84850463	44	74	0.59054233	39	97	0.39803553
80	6	1.5294118	52	13	1	31	52	0.84328033	107	75	0.58849399	67	98	0.38917901
41	7	1.306763	64	13	1	96	53	0.82003173	81	76	0.57771623	115	99	0.374154
45	8	1.2853258	66	13	1	108	54	0.81726094	58	77	0.57679494	1	100	0.37047866
83	9	1.2086956	71	13	1	111	55	0.81142452	105	78	0.56621046	112	101	0.36103124
26	10	1.1322636	72	13	1	53	56	0.80681012	50	79	0.5620658	51	102	0.36096889
109	11	1.0958577	73	13	1	47	57	0.80579527	3	80	0.56055283	92	103	0.35788511
84	12	1.0827967	75	13	1	106	58	0.74787362	2	81	0.53481983	27	104	0.3276777
8	13	1	76	13	1	48	59	0.74147996	13	82	0.52225037	15	105	0.27492907
11	13	1	77	13	1	7	60	0.73559787	93	83	0.52152339	100	106	0.25199846
14	13	1	78	13	1	59	61	0.71707895	82	84	0.50320452	69	107	0.23178621
16	13	1	85	13	1	97	62	0.70745959	62	85	0.50110212	10	108	0.20650682
17	13	1	87	13	1	9	63	0.70605276	6	86	0.49159373	33	109	0.20650682
19	13	1	90	13	1	94	64	0.68987501	98	87	0.47513516	74	110	0.20402824
21	13	1	91	13	1	102	65	0.68117598	103	88	0.47440186	61	111	0.20353869
23	13	1	95	13	1	28	66	0.66201662	60	89	0.45543838	68	112	0.1770921
24	13	1	57	44	0.99443054	63	67	0.63495079	5	90	0.44884999	113	113	0.17612853
25	13	1	4	45	0.99369193	114	68	0.63121715	70	91	0.43720876	54	114	0.17512331
29	13	1	65	46	0.90015285	56	69	0.62796032	79	92	0.43702871	49	115	0.14632709

After calculating and ranking of DMUs assisted by super-efficiency and based on the data presented in Tables 7 and 17, in Table 18, we've performed a thorough evaluation of all ten PSCs, assessing the average technical efficiency of patients who utilized services at each respective center. This examination offers valuable insights into how effectively and efficiently these centers provide care to their specific patient populations.

Table 18: Ranking of Ten Primary Stroke Centres After Applying Super-efficiency.

PSCs	Ranking	Ave. Efficiency Score
1	7	0.602416037
2	3	0.660644276
3	5	0.65294247
4	6	0.62440989
5	9	0.415850205
6	8	0.491534278
7	4	0.639572405
8	1	1.265286868
9	2	0.781811868
10	10	0.41100162

This ranking is based on the calculated efficiency scores for each PSC. PSC 8 has achieved the highest efficiency score of 1, indicating optimal performance. PSC 10 on the other hand, has the lowest efficiency score. The phenomenon of obtaining the same lowest and highest rankings in a super efficiency analysis, despite seemingly contradictory, underscores the critical influence of distance in the efficiency outcomes. When both the lowest and highest rankings remain consistent, it implies that certain entities, in this case, PSCs, are not only achieving optimal efficiency but are also strategically located near CSCs. The highest efficiency score indicates that the PSCs in question are operating at the peak of efficiency, effectively utilizing resources, and achieving optimal outcomes within the specified inputs and outputs. The lowest efficiency score, obtained by entities situated farther away, suggests that increased distance negatively affects efficiency, likely leading to higher transmission losses, extended response times, and potentially suboptimal operational outcomes. This phenomenon emphasizes the crucial role of geographical factors, particularly distance, in shaping the overall efficiency of the stroke care network. The consistent super efficiency rankings highlight that the spatial proximity to the CSC is a key determinant of optimal performance. Proximity allows for quicker response times, more efficient collaboration, and streamlined patient transfer processes, contributing to the overall effectiveness of the stroke care system. To further enhance efficiency, strategies aimed at minimizing distances between PSCs and CSCs could be considered. This might involve reevaluating the geographic distribution of stroke centers, optimizing their locations to ensure strategic coverage, and reducing potential barriers that could impede timely and effective stroke care delivery. In doing so, healthcare systems can leverage these insights to create more resilient and responsive stroke care networks, improving outcomes for patients across the spectrum of stroke cases.

3.4.2 Second Scenario

In the second phase of the analysis, eight PSCs with low patient volumes were combined into four DMUs, each comprising two PSCs. These selected PSCs not only had a limited number of patients, but they were also in close geographical proximity to one another. Two PSCs were kept separate due to their sufficient patient volume. The first phase of the analysis utilized VRS to generate efficiency scores for evaluation, whereas in the second phase, CRS proved to be more effective, providing improved results. Initially, ten PSCs were considered as six DMUs in the second phase, employing the input-oriented CRS approach for a total of 115 patients. Table 19 shows the average amount(or the number of inputs and outputs for the binary variables like thrombolysis given or not as well as EVT performed or not) of following inputs and outputs for the six suggested DMUs:

Input 1 (Age), Input 2 (ASPECTS), Input 3 (Collateral), Input 4 (Driving Distance), Input 5 (Euclidean Distance), Input 6 (Ave. Onset_To_Arrival_1st), Input 7 (Ave. DIDI Time(Door-In-Door-In), Input 8 (Ave. Onset_to_1st_CT), Input 9 (Number of Thrombolysis not given, and given), and Output 1(Number of EVT not performed and performed, and given). However, based on the second part of the first scenario we consider the critical inputs in this part including Driving Distance, Euclidean Distance, Ave. Onset_To_Arrival_1st, Ave. DIDI Time, Ave. Onset_to_1st_CT, and Number of Thrombolysis not given.

Table 19: The Average Amount of Inputs and Output for the Six Suggested DMUs.

DMUs	Ave. Age	Ave. ASPECTS	Ave. Collateral	Ave. Driving Distance	Ave. Euclidean Distance	Ave. Onset_To_Arrival_1st	Ave. DIDI Time(Door-In-Door-In)	Ave. Onset_to_1st_CT	Number of Thrombolysis not given	Number of Thrombolysis given	Number of EVTs not performed	Number of EVTs performed
1	51.6	8.2	2.6	400	312.58	338	514	508.8	4	1	3	2
2	69.5	8.25	2.5	105.4875	88.4375	269.125	227.625	296.125	2	6	2	6
3	70.5	8.5	3	217	166.9	110	230	129	1	1	1	1
4	68.875	9.5	2.75	193.25	151.1025	87.375	472	216.125	5	3	3	5
5	61.4	8.5333	2.4	8	3.28	453.5333	323.7333	526.1333	14	1	13	2
6	65	8.9333	2.6	105	87.4	118	199.4666	185.8	4	11	6	9

The statistical evaluations for suggested inputs and outputs including Mean, Sum, Standard Deviation, Variance, Min, Max, and Rang are presented in Table 20.

Table 20: Statistical Evaluations for Suggested Inputs and Output.

Variables	Mean	Sum	Std. Dev	Variance	Min	Max	Range
Input 1	64.48	386.88	7.16	51.28	51.6	70.5	18.9
Input 2	8.65	51.92	0.49	0.24	8.2	9.5	1.3
Input 3	2.64	15.85	0.21	0.04	2.4	3	0.6
Input 4	171.46	1028.74	134.36	18053.54	8	400	392
Input 5	134.95	809.7	104.49	10919.11	3.28	312.58	309.3
Input 6	229.34	1376.03	148.62	22089.04	87.38	453.53	366.16
Input 7	327.8	1966.82	135.31	18309.99	199.47	514	314.53
Input 8	310.33	1861.98	169.37	28685.21	129	526.13	397.13
Input 9	5	30	4.65	21.6	1	14	13
Input 9	3.83	23	4.02	16.17	1	11	10
Output 10	4.67	28	4.41	19.47	1	13	12
Output 10	4.17	25	3.06	9.37	1	9	8

These statistics provide a comprehensive overview of the distribution, variability, and central tendencies within each variable. The mean gives us an average value, the standard deviation indicates the spread of values around the mean, and the range represents the difference between the maximum and minimum values. Understanding these descriptive statistics is essential for gaining insights into the characteristics and patterns of your dataset, which can inform further analysis and decision-making processes.

3.4.2.1 CRS and VRS Input-oriented Assisted by Super-efficiency for Six DMUs

During the first part of the second phase, an assessment was conducted on ten PSCs, which were consolidated into six DMUs using the input-oriented CRS approach, considering a total of 115 patients. Additionally, super-efficiency measures were implemented in this stage to improve the evaluation process. Table 21 shows efficiency and super-efficiency results for 6 DMUs in CRS input-oriented model.

Table 21: Efficiency and Super-efficiency Results for Six DMUs in CRS Input-oriented Model.

DMUs	Efficiency T1 (2018-2019)	Super-efficiency of T1 (2018-2019)	Efficiency T2 (2020-2021)	Super-efficiency of T2 (2020-2021)
1	0.5	0.5	0.4615	0.4615
2	0.6667	0.6667	0.1811	0.1811
3	0.6667	0.6667	0.3946	0.3946
4	0.6753	0.6753	1	2.7572
5	1	5.7733	1	5.9269
6	1	1.7344	0.2846	0.2845

The performance analysis across the six DMUs reveals distinctive efficiency patterns. DMU 1, initially operating at full efficiency in T1, encountered a substantial decline to 46.15% in T2, indicating potential changes in inputs or outputs affecting its operational efficacy. Similarly, DMU 2 faced a significant efficiency drop from 66.67% in T1 to 18.11% in T2, suggesting operational challenges or shifts in the second period. DMU 3 experienced a decrease from 66.67% (T1) to 39.46% (T2), with a modest improvement, reflecting a nuanced performance evolution. In contrast, DMU 4 operated close to full efficiency in T1 (67.53%) and achieved a remarkable 100% efficiency in T2, surpassing the efficiency benchmark. DMU 5 demonstrated consistent full efficiency in both periods, and its super-efficiency scores exceeded already high standards, showcasing exceptional performance. DMU 6, efficient in T1, underwent a notable drop to 28.46% in T2, signaling potential issues or alterations in operations. General observations highlight efficiency fluctuations for DMUs 1, 2, 3, and 6, warranting further investigation into the factors influencing these changes. Super-efficiency analysis emphasizes exceptional performance for DMUs 1, 4, 5, and 6, as they either met or exceeded efficiency benchmarks in both periods. Recommendations include a comprehensive exploration of the factors contributing to efficiency changes for DMUs 1, 2, 3, and 6. Moreover, an in-depth analysis of super-efficiency scores could provide valuable insights into the practices and strategies employed by these highly efficient DMUs, potentially offering avenues for enhancing overall efficiency across the board.

Efficiency and super-efficiency results for 6 DMUs in VRS input-oriented model are demonstrated in Table 22.

Table 22: Efficiency and Super-efficiency Results for Six DMUs in VRS Input-oriented Model.

DMUs	Efficiency T1 (2018-2019)	Super-efficiency of T1 (2018-2019)	Efficiency T2 (2020-2021)	Super-efficiency of T2 (2020-2021)
1	0.55	0.55	1	1.1666667
2	1	1.4117538	1	1.6349027
3	1	2.2647356	0.9419	1.0957858
4	1	1.2955651	1	3
5	1	Infeasible	1	Infeasible
6	1	1.8477036	0.8993	1.080464

In the VRS input-oriented model for the six DMUs, DMU 1 exhibited an efficiency increase from 55% in T1 to 100% in T2, with a super-efficiency score of 1.1666667 in the second period. This suggests that DMU 1 not only achieved full efficiency but surpassed it, indicating outstanding performance. DMU 2 maintained full efficiency in both periods, with super-efficiency scores of 1.4117538 in T1 and 1.6349027 in T2, showcasing consistent high-level performance. DMU 3 was fully efficient at 2.2647356 but super-efficiency score of 2.2647356 but experienced a slight decrease to 94.19% efficiency in T2, reflected in a super-efficiency score of 1.0957858. DMU 4 operated at full efficiency in both periods, with a super-efficiency score increasing from 1.2955651 in T1 to 3 in T2, exceeding the already high efficiency benchmarks. DMU 5 encountered infeasibility in both efficiency and super-efficiency calculations in both periods. DMU 6 achieved full efficiency in T1, with a super-efficiency score of 1.8477036, but its efficiency dropped to 89.93% in T2, resulting in a super-efficiency score of 1.080464. General observations indicate variations in efficiency performance across the DMUs. Recommendations include a thorough investigation into the factors influencing efficiency changes, especially for DMUs 3, 5, and 6, where notable fluctuations or infeasibility occurred. Additionally, analyzing super-efficiency scores for DMUs 1, 2, 3, and 4 can provide insights into their practices and strategies that contribute to outstanding performance, potentially offering valuable lessons for enhancing overall efficiency.

As the CRS model identified additional inefficient DMUs, we proceeded to conduct a more in-depth exploration of the following four tables in CRS input-oriented approach, assisted by super-efficiency analysis, spanning two distinct periods, namely 2018-2019 and 2020-2021.

Appendix B (Table 33) covers the VRS input-oriented analysis for the two specified periods (2018-2019 and 2020-2021 in the Second Scenario).

An analysis of Table 23, which represents the DEA evaluation under the CRS-2018-2019 model, reveals key insights into the efficiency and ranking of the six DMUs. DMUs 1, 2, 3, and 4 exhibited efficiency scores ranging from 0.5 to 0.6753, suggesting room for improvement in their resource utilization. DMUs 5 and 6, however, achieved perfect efficiency scores of 1, signifying optimal performance. The reference set, denoted by the efficient DMU number, varied across the entities, with DMU 5 referencing 5 efficient DMUs, while DMU 6 referenced all 6 efficient DMUs. Peer weights (Lambdas) indicate the influence of each peer in the evaluation process, with higher weights suggesting greater impact. Peer counts represent the number of peers considered for each DMU, influencing the relative importance of peer contributions. The classification distinguishes between CRS and IRS, providing insights into the underlying model applied. Rankings further highlight the performance order, with DMUs 5 and 6 securing the top positions, indicating their superior efficiency. Overall, the table serves as a comprehensive overview of the DEA analysis, encompassing efficiency scores, reference sets, peer weights, classifications, and rankings for each DMU in the CRS-2018-2019 context.

Table 23: Reference Set, Peer Weight, Peer Count, and Classification of Six DMUs in CRS Input-oriented Model During 2018-2019.

DMUs	Efficiency	Reference Set (Efficient DMUs number)	Peer Weight (Lambdas)	Peer Count	Classification	Ranking
1	0.5	6	0.5	-	IRS	4
2	0.6667	6	0.33333333	-	IRS	3
3	0.6667	6	0.16666667	-	IRS	3
4	0.6753	6	0.5	-	IRS	2
5	1	5	1	1	CRS	1
6	1	6	1	5	CRS	1

Analyzing the super-efficiency results for the DMUs in the CRS-2018-2019 model in Table 24 reveals distinctive performances. DMUs 1, 2, 3, and 4, classified under IRS (Increasing Returns to Scale), did not have applicable super-efficiency scores. In contrast, DMU 5 showcased outstanding efficiency with a score of 5.773374 and a DRS classification, securing the top ranking. DMU 6, with a super-efficiency score of 1.7344792 and an IRS classification, ranked second. The inclusion of reference sets and peer weights, particularly for DMU 6 involving DMUs 4 and 5, contributed to its exceptional super-efficiency performance. Overall, super-efficiency analysis highlights the exceptional performance of DMUs 5 and 6, providing valuable insights for further exploration of their strategies and practices to enhance overall efficiency.

Table 24: Reference Set, Peer Weight, Peer Count, and Classification of Six DMUs in CRS Input-oriented Model During 2018-2019 After Applying Super-efficiency.

DMUs	Efficiency	Reference Set (Efficient DMUs	Peer Weight (Lambdas)	Peer Count	Classification	Ranking
1	0.5	6	0.5	-	IRS	5
2	0.66666667	6	0.33333333	-	IRS	4
3	0.66666667	6	0.16666667	-	IRS	4
4	0.67525036	6	0.5	-	IRS	3
5	5.773374	6	2.1666667	1	DRS	1
6	1.7344792	4,5	0.26925738,0.39940214	5	IRS	2

Observing Table 25 for the DEA evaluation under the CRS-2020-2021 model reveals the efficiency and ranking of the six DMUs. DMU 1, with an efficiency of 0.4615, referencing only DMU 4, obtained a peer weight of 0.23076923. Classified under IRS (Increasing Returns to Scale), it secured a ranking of 2. DMU 2 demonstrated an efficiency of 0.1811, referencing only DMU 4 with a peer weight of 0.070166432. Despite its IRS classification, DMU 2 obtained a ranking of 5. DMU 3, with an efficiency of 0.3946, also referenced DMU 4 as the only efficient DMU, obtaining a peer weight of 0.30769231, resulting in a ranking of 3. DMU 4 and DMU 5 both achieved perfect efficiency scores of 1, referencing only DMU 4 and DMU 5 as efficient DMUs, respectively, and obtaining top rankings under the CRS classification. DMU 6, with an efficiency of 0.2846, referenced only DMU 4, securing a peer weight of 0.12432423. Despite an IRS classification, DMU 6 obtained a ranking of 4. The table provides a comprehensive overview of efficiency, reference sets, peer weights, classifications, and rankings for each DMU in the CRS-2020-2021 context.

Table 25: Reference Set, Peer Weight, Peer Count, and Classification of Six DMUs in CRS Input-oriented Model During 2020-2021.

DMUs	Efficiency	Reference Set (Efficient DMUs	Peer Weight (Lambdas)	Peer Count	Classification	Ranking
1	0.4615	4	0.23076923	1	IRS	2
2	0.1811	4,5	0.070166432, 0.00627403	2	IRS	5
3	0.3946	4	0.30769231	1	IRS	3
4	1	4	1	5	CRS	1
5	1	5	1	3	CRS	1
6	0.2846	4,5	0.12432423, 0.02741322	2	IRS	4

Examining Table 26, which represents the super-efficiency results for the CRS-2020-2021 model, provides insights into the efficiency and ranking of the six Decision Making Units (DMUs). DMU 1, with an efficiency of 0.4615, referenced DMU 4 as the efficient DMU and achieved a peer weight of 0.23076923. Despite its IRS classification, DMU 1 obtained a ranking of 3. DMU 2, with an efficiency of 0.1811, referenced both DMU 4 and DMU 5 as efficient DMUs, securing respective peer weights of 0.070166432 and 0.006274027. This IRS-classified DMU obtained a ranking of 6. DMU 3, with an efficiency of 0.3946, referenced DMU 4 as the efficient DMU and obtained a peer weight of 0.30769231, resulting in a ranking of 4. DMU 4 demonstrated super-efficiency with a score of 2.7572, referencing DMUs 1 and 5 as efficient peers and obtaining respective peer weights of 1.326589 and 0.64430236. This DRS-classified DMU secured a ranking of 2. DMU 5 showcased exceptional super-efficiency with a score of 5.9269, referencing DMU 4 as the efficient peer and achieving a peer weight of 1.0769231. This top-ranked DRS-classified DMU outperformed all others. DMU 6, with an efficiency of 0.2845, referenced both DMU 4 and DMU 5 as efficient peers, securing respective peer weights of 0.12432423 and 0.027413215. Despite its IRS classification, DMU 6 obtained a ranking of 5. The table offers a comprehensive view of super-efficiency, reference sets, peer weights, classifications, and rankings for each DMU in the CRS-2020-2021 context.

Table 26: Reference Set, Peer Weight, Peer Count, and Classification of Six DMUs in CRS Input-oriented Model During 2020-2021 After Applying Super-efficiency.

DMUs	Efficiency	Reference Set (Efficient DMUs	Peer Weight (Lambdas)	Peer Count	Classification	Ranking
1	0.4615	4	0.23076923	-	IRS	3
2	0.1811	4,5	0.070166432,0.006274027	-	IRS	6
3	0.3946	4	0.30769231	-	IRS	4
4	2.7572	1,5	1.326589, 0.64430236	5	DRS	2
5	5.9269	4	1.0769231	3	DRS	1
6	0.2845	4,5	0.12432423, 0.027413215	-	IRS	5

3.4.2.2 Analysis of Malmquist Productivity Index for the Second Scenario

In this part, a comparison between the first period (2018-2019) and the second period (2020-2021) was conducted using the MPI including CRS and VRS to evaluate the relative efficiency and productivity change of six DMUs across different time periods. Table 27 shows MPI results for CRS input-oriented model.

Table 27: Malmquist Productivity Index Results for Six DMUs Considering CRS Input-oriented Between T1(2018-2019) and T2(2020-2021).

DMUs	TC	EC	T2D1CRS	T1D2CRS	TFPG (MI)	Efficiency T1	Efficiency T2
1	1.87	0.92	0.27	0.86	1.72	50	46.15
2	1.66	0.27	0.38	0.29	0.45	66.67	18.11
3	1.65	0.59	0.36	0.57	0.98	66.67	39.46
4	1.5	1.48	0.56	1.87	2.23	67.53	100
5	1.02	1	1.59	1.65	1.02	100	100
6	1.09	0.28	1.13	0.38	0.31	100	28.46

In this study, MPI is used to evaluate the productivity change between two time periods for a set of DMUs. In this study, six DMUs are compared in two periods including 2018-2019 and 2020-2021.

Let's break down and compare the results for MPI, CRS input oriented in Table 27:

Total Change measures the overall productivity change. It is a weighted average of TC and

EC. EC represents the change in efficiency. It's a measure of how much more efficiently the DMUs are utilizing their inputs in the second period compared to the first period. TC represents the technology change. It's a measure of how much the production technology has changed over the two periods. Technical Efficiency Change (T2D1CRS) is a component of the TC that measures the change in efficiency while holding the technology constant. Technical Efficiency Change (T1D2CRS) is a factor of the TC that calculates the change in technology while holding efficiency constant. Finally, Total Factor Productivity Growth (TFPG(MI)) is a measure of how much output can be produced with a given set of inputs. It is a combination of technological change and efficiency change.

Here is a detailed comparison of the results for DMUs 1 to 6 for CRS input-oriented MPI:

DMU 1:

Considering, TC: 1.87, EC: 0.92, Efficiency T1: 0.5, Efficiency T2: 0.0.4615, and MI:1.72

T2D1CRS (Technical Efficiency T2 relative to T1 in CRS): 0.27 - Suggests a technical change, implying decline in technical efficiency in utilizing inputs for output production in the second period (T1 is more efficient than T2).

T1D2CRS (Technological Efficiency T1 relative to T2 in CRS): 0.86 - Indicates an improvement in technological efficiency, meaning DMU 1 was more efficient in producing higher outputs relative to inputs in the second period (T2 is more efficient than T1).

DMU 2:

T2D1CRS (Technical Efficiency T2 relative to T1 in CRS): 0.38 - Suggests a technical change, implying decline in technical efficiency in utilizing inputs for output production in the second period (T1 is more efficient than T2).

T1D2CRS (Technological Efficiency T1 relative to T2 in CRS): 0.29 - Indicates an improvement in technological efficiency, though to a lesser extent than DMU 1 (T2 is more efficient than T1).

DMU 3:

T2D1CRS (Technical Efficiency T2 relative to T1 in CRS): 0.36 - Suggests a technical change, implying a decline in technical efficiency in utilizing inputs for output production in the second period (T1 is more efficient than T2).

T1D2CRS (Technological Efficiency T1 relative to T2 in CRS): 0.57 - Indicates an improvement in technological efficiency, but it's important to note that there may be other issues in the dataset (T2 is more efficient than T1).

DMU 4:

T2D1CRS (Technical Efficiency T2 relative to T1 in CRS): 0.56 - Suggests a minimal technical change, suggesting relatively stable utilization of resources.

T1D2CRS (Technological Efficiency T1 relative to T2 in CRS): 1.87 - Indicates a substantial improvement in technological efficiency, signifying a significant increase in output relative to inputs.

In evaluating the MPI results for the six suggested DMUs over the transition from T1 (2018-2019) to T2 (2020-2021) based on the CRS input-oriented approach, notable patterns emerge. DMU 1 demonstrates an overall productivity improvement (MPI = 1.72) driven by positive technological change (T1D2CRS = 0.86) and a moderate decline in technical efficiency (T2D1CRS = 0.27). Conversely, DMU 2 exhibits a decline in productivity (MPI = 0.45) attributed to a decline in technical efficiency (T2D1CRS = 0.38) and minor technological change (T1D2CRS = 0.29). DMU 3 shows a modest decrease in productivity (MPI = 0.98) stemming from diminished technical efficiency (T2D1CRS = 0.36) despite positive technological change (T1D2CRS = 0.57). In contrast, DMU 4 experiences substantial productivity growth (MPI = 2.23) due to a significant increase in technological change (T1D2CRS = 1.87). DMU 5 maintains relatively stable productivity (MPI = 1.02) with substantial gains in technical efficiency (T2D1CRS = 1.59) and positive technological change (T1D2CRS = 1.65). Finally, DMU 6 exhibits a decline in productivity (MPI = 0.31) resulting from technical efficiency (T2D1CRS = 1.13) and technological change (T1D2CRS = 0.38). These evaluations highlight the varying dynamics of productivity changes among the DMUs, emphasizing the importance of considering both technical and technological factors in assessing overall efficiency.

Table 28 shows MPI results for VRS input-oriented model.

Let's break down the results for MPI, VRS input oriented in Table 28:

SEC represents the change in scale efficiency. It's a measure of how well the DMUs are operating at their optimal scale. PEC is a component of the SEC that measures the change in efficiency due to scale changes. Technical Efficiency Change (T2D2CRS) is a component of the TC that measures the change in efficiency while allowing for changes in scale. Technical Efficiency Change (T1D1CRS) is a component of the TC that measures the change in technology while holding scale efficiency constant. Technical Efficiency Change (T2D1VRS) is a factor of the TC that calculates the change in efficiency while allowing for changes in scale. Technical Efficiency Change (T1D2VRS) is a factor of the TC that quantifies the alteration in technology while holding scale efficiency constant.

Table 28: Malmquist Productivity Index Results for Six DMUs Considering VRS Input-oriented Between T1(2018-2019) and T2(2020-2021).

DMUs	TC	SEC	PEC	T2D2CRS	T1D1CRS	T2D1VRS	T1D2VRS	T2D1CRS	T1D2CRS	TFPG (MI)	Efficiency T1	Efficiency T2
1	0.91	1.04	1.82	0.46	0.5	0.64	0.96	0.27	0.86	1.72	55	100
2	0.94	0.48	1	0.18	0.67	1.23	1.09	0.38	0.29	0.45	100	100
3	0.58	1.79	0.94	0.39	0.67	2.15	0.68	0.36	0.57	0.98	100	94.19
4	1.14	1.95	1	1	0.68	2.25	2.94	0.56	1.87	2.23	100	100
5	1.02	1	1	1	1	1.59	1.66	1.59	1.65	1.02	100	100
6	0.75	0.46	0.9	0.28	1	1.77	0.89	1.13	0.38	0.31	100	89.93

Here is a detailed comparison of the results for DMUs 1 to 6 for VRS input-oriented MPI:

DMU 1:

Considering, TC: 0.91, SEC: 1.04, PEC: 1.82, Efficiency T1: 55, Efficiency T2: 100, and MI: 1.72

T2D1VRS (Technical Efficiency T2 relative to T1 in VRS): 0.64 - Indicates a positive technical change, showcasing an improvement in resource utilization and output production in the second period (T1 is more efficient than T2 in the use of variable inputs).

T1D2VRS (Technological Efficiency T1 relative to T2 in VRS): 0.96 - Indicates an improvement in technological efficiency, signifying an increase in output relative to inputs (T2 is more efficient than T1 in the use of variable inputs).

DMU 2:

T2D1VRS (Technical Efficiency T2 relative to T1 in VRS): 1.23 - Indicates an improvement in technical efficiency and better resource utilization for output production in the second period (T2 is more efficient than T1 in the use of variable inputs).

T1D2VRS (Technological Efficiency T1 relative to T2 in VRS): 1.09 - Indicates an improvement in technological efficiency, although not as substantial as in CRS (T1 is more efficient than T2 in the use of variable inputs).

DMU 3:

T2D1VRS (Technical Efficiency T2 relative to T1 in VRS): 2.15 - Indicates a positive technical change, showcasing an improvement in resource utilization and output production in the second period (T2 is more efficient than T1 in the use of variable inputs).

T1D2VRS (Technological Efficiency T1 relative to T2 in VRS): 0.68 - Indicates an improvement in technological efficiency, suggesting better conversion of inputs to outputs (T2 is more efficient than T1 in the use of variable inputs).

DMU 4:

T2D1VRS (Technical Efficiency T2 relative to T1 in VRS): 2.25 - Indicates an improvement in technical efficiency and better resource utilization for output production in the second period (T2 is more efficient than T1 in the use of variable inputs).

T1D2VRS (Technological Efficiency T1 relative to T2 in VRS): 2.94 - Indicates a substantial improvement in technological efficiency, indicating a significant increase in output relative to inputs (T1 is more efficient than T2 in the use of variable inputs).

DMU 5:

T2D1VRS (Technical Efficiency T2 relative to T1 in VRS): 1.59 - Indicates a substantial improvement in technical efficiency, suggesting higher outputs with the same inputs (T2 is more efficient than T1 in the use of variable inputs).

T1D2VRS (Technological Efficiency T1 relative to T2 in VRS): 1.66 - Indicates an improvement in technological efficiency, signifying that DMU 5 became more efficient in producing outputs (T1 is more efficient than T2 in the use of variable inputs).

DMU 6:

T2D1VRS (Technical Efficiency T2 relative to T1 in VRS): 1.77 - Indicates an improvement in technical efficiency, suggesting better resource utilization for output production in the second period (T2 is more efficient than T1 in the use of variable inputs).

T1D2VRS (Technological Efficiency T1 relative to T2 in VRS): 0.89 - Indicates an improvement in technological efficiency, signifying an improvement in resource utilization and output production (T2 is more efficient than T1 in the use of variable inputs).

In evaluating the MPI results for the six suggested DMUs over the transition from T1 (2018-2019) to T2 (2020-2021) based on the VRS input-oriented approach, notable patterns emerge. DMU 1 demonstrates an overall productivity improvement (MPI = 1.72) driven by positive technological change (T1D2VRS = 0.96) and a positive technical change

(T2D1VRS = 0.64). DMU 2 exhibits a decline in productivity (MPI = 0.45) with TC and SEC less than one. DMU 3 shows a decline in productivity (MPI = 0.98) with TC and SEC less than one. In contrast, DMU 4 experiences substantial productivity growth (MPI = 2.23) due to a significant improvement in both technical efficiency (T2D1VRS = 2.25) and technological change (T1D2VRS = 2.94). DMU 5 maintains relatively stable productivity (MPI = 1.02) with substantial gains in technical efficiency (T2D1VRS = 1.59) and positive technological change (T1D2VRS = 1.66). Finally, DMU 6 exhibits a significant decline in productivity (MPI = 0.31) by multiplying TC, SEC, and PEC which are less than one. These evaluations highlight the varying dynamics of productivity changes among the DMUs, emphasizing the importance of considering both technical and technological factors in assessing overall efficiency.

The detailed comparisons provide insights into how each DMU performed in terms of technical efficiency, technological efficiency, and overall productivity change over the two periods under both CRS and VRS assumptions. The values offer specific indications of improvements or stability in resource utilization and output production for each DMU. The CRS and VRS methods provide slightly different perspectives on productivity change and efficiency for the DMUs. VRS allows for a more nuanced analysis by considering scale efficiency changes. The choice between CRS and VRS may depend on the specific characteristics and context of the DMUs. For example, if scale efficiency is a critical factor, VRS may provide more relevant insights. It's important to note that the interpretation of these results should be done in conjunction with a thorough understanding of the specific context and operations of the DMUs in question. Additionally, the results may be influenced by the assumptions and methodology used in the analysis.

3.5 Discussions

The detailed comparisons provide insights into how each DMU performed in terms of technical efficiency, technological efficiency, and overall productivity change over the two periods under both CRS and VRS assumptions. The values offer specific indications of improvements or stability in resource utilization and output production for each DMU. The CRS and VRS methods provide slightly different perspectives on productivity change and efficiency for the DMUs. VRS allows for a more nuanced analysis by considering scale efficiency changes. The choice between CRS and VRS may depend on the specific characteristics and context of the DMUs. For example, if scale efficiency is a critical factor,

VRS may provide more relevant insights. It's important to note that the interpretation of these results should be done in conjunction with a thorough understanding of the specific context and operations of the DMUs in question. Additionally, the results may be influenced by the assumptions and methodology used in the analysis.

In examining the results across two distinct scenarios, the pivotal role of the distance between PSCs and the CSC becomes apparent. Specifically, in the first scenario, PSC 8 corresponds to DMU 5 in the second scenario. Possessing the shortest distance to the CSC, PSC 8 secures the top position and attains the highest efficiency score in all CRS and VRS models within both scenarios. Similarly, PSC 9 in the first scenario aligns with DMU 5 in the second scenario. As the second closest PSC to the CSC, it claims the second position in all aspects of the first scenario and dominates in most segments of the second scenario. Conversely, PSC 10 and 5 exhibits the longest distance from the CSC (as evident from Table 3, where the combination of these two PSCs forms DMU 1 in the second scenario). Unsurprisingly, they register the lowest efficiency scores in all facets of the first scenario and a substantial portion of the second scenario. This detailed analysis underscores the critical influence of proximity to the CSC on the efficiency and performance of EVT treatment in stroke care, shedding light on specific PSCs that excel or face challenges based on their geographic positioning in relation to the comprehensive treatment center.

It should be noted that in some cases, despite longer distances to CSCs, certain PSCs may exhibit higher efficiency scores. In the healthcare sector, optimizing the balance between distance and efficiency involves a multidimensional approach that considers not only physical proximity but also the capabilities, resources, and coordination among healthcare facilities. Regional healthcare systems often work to ensure that patients have access to the right level of care based on their needs and the severity of their condition, considering the geographical distribution of healthcare facilities. While CSCs may offer specialized care, the efficiency of patient outcomes is influenced by factors such as timely transportation, telemedicine advancements for remote consultations, regional collaboration ensuring smooth patient transfer, resource allocation at PSCs, and adherence to quality metrics in healthcare. Even when located at a greater distance, efficient resource management, effective communication, and a focus on quality care can contribute to higher efficiency scores for some PSCs compared to their closer CSC counterparts. The multidimensional nature of healthcare systems requires a careful balance between physical proximity and the quality and coordination of care to optimize patient outcomes.

3.6 Conclusion, Limitations, and Future Studies

Stroke is a disease that disproportionally affects an older population, and it is the leading cause of severe disability. Improved patient outcomes for the most severe ischemic stroke patients through this project will allow older Nova Scotians to age in place. Reducing disability for severe ischemic stroke patients can be achieved by increasing the number of patients living outside of Halifax that receive EVT. This improvement will avoid the need for long term care or lengthy inpatient rehabilitation; therefore, they will be able to remain in rural areas with their families in locations where they reside. This study applied DEA to improve the efficiency of ischemic stroke patient transfers for EVT within PSC in a small Canadian province. The research provided valuable insights into healthcare delivery across two distinct periods, showcasing DEA's important role as a decision-support tool for healthcare policy and resource allocation. To address data limitations stemming from the province's size, PSCs were strategically combined to bolster patient sample sizes for comprehensive analysis. The study focused on a range of inputs, including age and distance metrics, relative to the pivotal output variable of EVT performance. Throughout the evaluation phases, both VRS and CRS methodologies were employed, with CRS ultimately yielding superior results in the latter phase. Additionally, the study conducted a comparative analysis between the two periods, employing the MPI to assess relative efficiency and productivity changes across six DMUs. While PyDEA facilitated the initial evaluations, PIM-DEA software was instrumental in conducting advanced MPI assessments over time. Distance plays a crucial role in stroke care efficiency, evident in the comparison of PSCs in different scenarios. PSC 8 (DMU 5 in the second scenario) stands out with the shortest distance to the CSC, securing the highest efficiency scores. In contrast, PSC 10 and 5, positioned farthest from the CSC, demonstrate the lowest efficiency scores. This highlights the pivotal influence of geographic proximity to the CSC on the efficiency and performance of specific PSCs in delivering EVT for strokes. The findings underscored the critical role of proximity in ensuring timely access to EVT, particularly in regions with substantial distances between PSCs and Comprehensive CSC equipped with EVT technology. This research provides a valuable foundation for future studies, which could expand the model to encompass larger provinces with multiple CSCs.

It is crucial to recognize specific limitations inherent in this research. A notable constraint stems from the relatively small size of the province under examination compared to larger provinces, such as Ontario, which have more extensive datasets available for analysis.. As a result, it became necessary to strategically combine several PSCs to bolster patient sample sizes. While this approach allowed for a more comprehensive analysis, it is essential to recognize that the available data may still have limitations in providing a complete representation of the province's healthcare landscape. Looking ahead, one promising avenue for future research lies in addressing these data restrictions. Conducting similar analyses in larger provinces or regions with more extensive healthcare infrastructures could offer a broader perspective. This expansion would likely lead to a more robust dataset, enabling researchers to draw more definitive conclusions and make more generalized recommendations. Moreover, a larger province may house a greater number of EVT centers, allowing for an even more nuanced evaluation of stroke care delivery. By applying the suggested model in this context, researchers may uncover additional insights and potential areas for improvement in healthcare delivery. Future studies could leverage the groundwork laid in this research to conduct even more comprehensive assessments on a larger scale.

3.7 Data Availability Statement

The authors declare that all supporting data are available within the article and its supplementary materials.

3.8 Author contributions

Methodology, N.K, and M.M.; Conceptualization, M.M., and N.K.; software, N.K, and M.M.; Investigation, M.M.; Resources, M.M., Writing—Original Draft Preparation, M.M.; Data curation, N.K, and M.M.; Writing—Review and Editing, N.K.; Visualization, M.M., and N.K.; Supervision, N.K.; Project Administration, N.K. All authors have read and agreed to the published version of the manuscript.

3.9 Supplementary Materials

The Supplementary materials for this article can be found in Appendix B.

CHAPTER 4 DISCUSSION

The two manuscripts that were completed explore the application of DEA in emergency care and the management of acute condition such as ischemic stroke. Paper 1 was a narrative review of the state of the art in applying DEA in emergency department treatment of urgent conditions such as acute ischemic stroke. Paper 2 applied DEA to the efficiency of transferring patients from PSCs to CSCs for EVT.

In Paper 1 (27), a narrative review categorizes DEA applications in EDs, emphasizing its utility in benchmarking patient treatment proportions and efficiency analysis. The study identifies five parts, including basic DEA models, advanced approaches, time series models, integration with other methodologies, and specific models for acute ischemic stroke management. Methodological insights encompass the use of VRS and CRS, super-efficiency models, and the incorporation of simulations and machine learning. The paper concludes by exploring ways to elevate DEA from a technical application to a robust methodology for healthcare decision-makers.

Paper 2 delves into a detailed application of DEA to address the challenge of minimizing transfer times and futile transfers for ischemic stroke patients transferred for EVT using Nova Scotia, Canada as a case study. The study is structured in two distinct phases. In the initial phase, each PSC is treated as an independent DMU, creating a comprehensive analysis for ten PSCs using an input oriented VRS assisted by super efficiency analysis. The use of super efficiency analysis is particularly noteworthy as it allows for the identification of outlier observations and enhances the evaluation process. This phase involves a meticulous consideration of nine inputs, including patient age and the distance between PSCs and the CSC providing EVT. The second phase strategically addresses data limitations arising from the relatively small size of Nova Scotia. Eight PSCs with low patient numbers are merged into four DMUs, each consisting of two PSCs. This strategic combination allows for a more comprehensive analysis by bolstering patient sample sizes. The decision to merge PSCs is based not only on the limited number of patients but also on geographic proximity, ensuring that PSCs selected for merging are close to one another. Two PSCs are kept separate due to their sufficient patient volume. In this phase, both VRS and CRS methodologies are employed, with CRS ultimately outperforming VRS and yielding superior results. The study goes beyond the immediate analysis of efficiency by conducting a comparative assessment between two distinct periods

(2018-2019 and 2020-2021) using the MPI. This temporal analysis aims to evaluate the relative efficiency and productivity changes of six DMUs over time. It is noteworthy that the study acknowledges the limitations of the Python-based PyDEA tool used in the initial phase for MPI evaluations over time and opts for PIM-DEA software, which provides the necessary advanced functionalities. The findings of both phases highlight the significant impact of considerable distances between specific PSCs and the CSC on the efficiency and performance of EVT delivery for stroke patients. Geographic proximity emerges as a critical factor influencing access times for EVT. The study not only contributes insights into healthcare delivery within a specific region but also underscores the broader implications of distance on emergency care efficiency. In summary, Paper 2 provides a meticulous and context-specific application of DEA, addressing practical challenges in stroke care delivery. By strategically merging PSCs and employing advanced methodologies, the study not only offers insights into Nova Scotia's healthcare landscape but also sets the stage for potential applications of DEA in larger provinces or regions with more extensive healthcare infrastructures.

Together, these papers contribute to a nuanced understanding of how DEA can be applied in emergency care settings. Paper 1 provides a comprehensive overview, categorizing DEA applications, while Paper 2 offers a specific case study, showcasing the practical implications of DEA in minimizing transfer times for ischemic stroke patients. The combination of these insights underscores the versatility and effectiveness of DEA as a decision-support tool for healthcare managers and decision-makers, offering both a broad perspective and a real-world application within the emergency care context.

4.1 Interpretation of DEA Results for Healthcare Administrators

Healthcare administrators in Nova Scotia face a critical decision-making challenge when interpreting the DEA results, especially with a single EVT center and ten Primary Stroke Centers (PSCs). The findings indicate that Eastern zones, being the furthest from the Comprehensive Stroke Center (CSC), exhibit lower efficiency scores. This geographical variation underscores the importance of spatial proximity in stroke care efficiency. Administrators should recognize that the reduced efficiency scores in Eastern zones may be attributed to longer distances, potentially leading to extended response times and logistical complexities. This prompts the need for strategic interventions to address geographical challenges and optimize the overall stroke care network.

- **Resource Allocation and EVT Center:**

Resource Utilization: With a single EVT center in Nova Scotia, administrators need to carefully allocate resources to ensure optimal utilization. The DEA results offer insights into the efficiency of resource allocation across centers, guiding administrators in identifying areas for improvement and ensuring that the EVT center is operating at its maximum capacity.

Benchmarking: The EVT center can serve as a benchmark for efficient practices. Decision-makers should investigate the factors contributing to its high efficiency score and consider replicating successful strategies in other centers to enhance overall system efficiency.

- **Strategic Planning for System-Wide Improvement:**

System-Wide Optimization: Administrators can use the DEA results to inform strategic planning initiatives aimed at system-wide improvement. This may involve standardizing protocols, implementing best practices from high-efficiency centers, and addressing inefficiencies in time metrics to elevate the overall quality of stroke care services.

Collaboration and Communication: Decision-makers should encourage collaboration and communication among stroke centers, fostering a network that shares best practices and collectively works towards enhancing the efficiency of the entire system. Regular assessments and adjustments based on performance metrics will be crucial for continuous improvement.

In summary, healthcare administrators in Nova Scotia, armed with DEA insights, can strategically optimize the stroke care network. Addressing geographical challenges, ensuring efficient resource allocation, and fostering collaboration among centers are key considerations for decision-makers aiming to enhance the overall effectiveness of stroke care services in the region.

4.2 Limitations and Future Direction of the Research

In reflecting upon the insightful findings presented in this case study, it is essential to acknowledge the research's efforts in applying DEA to address the challenges of minimizing transfer times and futile transfers of ischemic stroke patients for EVT. The study's two-phase approach, incorporating strategic merging of PSCs and employing VRS and CRS methodologies, offers valuable contributions to the understanding of healthcare efficiency within a specific regional context. However, as with any research endeavor, certain limitations arise, particularly stemming from the small number of patients and resultant data constraints. Additionally, the study prompts thoughtful considerations for future research directions, suggesting avenues for addressing these limitations and broadening the scope to larger provinces and larger datasets, thereby enhancing the applicability and generalizability of the DEA model in diverse healthcare settings. In the following, we highlighted the suggested limitations and future directions:

The limitations in this study include:

1. **Data Representation Challenges:**

   - While the strategic combination of PSCs allows for a more comprehensive analysis, it is crucial to acknowledge that the available data may still have limitations in providing a complete and nuanced representation of the entire healthcare landscape within Nova Scotia. The merged PSCs may not fully capture the diversity and intricacies of individual centers, potentially impacting the generalizability of the study's findings.

2. **Geographic Specificity:**

   - The research's geographic specificity to Nova Scotia might limit the generalizability of its findings to other regions with distinct healthcare infrastructures. The unique characteristics of Nova Scotia, such as its size and population density, may not be representative of larger provinces or regions, affecting the applicability of the proposed model in diverse healthcare contexts.

In essence, future research should build upon the limitations identified in this research by expanding the scope to larger provinces, addressing data restrictions, and ensuring the applicability of the DEA model in varied healthcare contexts. This approach will contribute to a more comprehensive understanding of the efficiency and performance of acute stroke systems across hospitals. While the study focuses on efficiency and geographic considerations, future research might delve into a comprehensive cost-benefit analysis associated with different transportation methods. Evaluating the economic implications, including infrastructure investment, maintenance costs, and potential healthcare savings through faster interventions, could provide a more holistic understanding of the viability of transportation improvements.

CHAPTER 5 CONCLUSION

The findings underscore the vital role of geographic proximity in influencing the efficiency and performance of specific PSCs in delivering EVT for stroke patients. Importantly, this insight holds considerable implications for future healthcare planning, suggesting that if the establishment of a second CSC is recommended, the Eastern zone should be a priority to address the extended transportation distances faced by PSCs in this region. Furthermore, the consideration of Euclidean distance for air transport from long distances reflects a pragmatic approach, recognizing the urgency of stroke cases where minutes are crucial. The recommendation for such rapid transportation methods aligns with the broader goal of minimizing transfer times and optimizing healthcare delivery. This aspect of the conclusion emphasizes the practical implications of the research, advocating for strategic improvements in the transportation infrastructure to enhance the overall efficiency of stroke care. In essence, this case study not only summarizes the efficiency trends among PSCs but also provides actionable insights for healthcare policymakers. The emphasis on geographic priority and the practical consideration of transportation methods adds a nuanced dimension to the research, contributing valuable guidance for future healthcare planning and resource allocation in the region.

5.1 Summary of Contributions

This research studied the application of DEA to optimize healthcare delivery and minimize transfer times for ischemic stroke patients receiving EVT. The contributions of this research are as follows:

1. **Geographic Efficiency and PSC Performance:**
    - **Geographic Efficiency Analysis:** Explores the relationship between geographic distance and PSC efficiency for delivering EVT to ischemic stroke patients.
    - **Strategic Merging for Nuanced Insights:** Merges PSCs based on patient volume and geographical proximity to provide comprehensive and nuanced insights into the efficiency landscape.
    - **Efficiency Variations Among PSCs:** Identifies specific PSCs demonstrating lower efficiency and highlights the pivotal role of geographic proximity.
    - **Eastern Zone Priority Recommendations:** It is recommended to prioritize the

Eastern zone for a potential second CSC, considering specific regional needs, Euclidean distance, or the requirement for helicopters in patient transportation, as well as the potential need for additional ambulances. The decision to prioritize the Northern zone is based on its acquisition of the second lowest average efficiency score for PSCs, designating it as the second priority.

2. **Patient-Centric Focus and Individualized Analysis:**

- **Patient-Centric Evaluation:** Treats each ischemic stroke patient as an independent DMU, offering a detailed analysis of individual experiences and outcomes.
- **Two-Scenario Analysis:** Conducts a dynamic analysis in two distinct scenarios, providing a nuanced understanding of efficiency trends considering different parameters.
- **Comparative Analysis Over Two Periods:** Offers insights into efficiency trends over time by comparing two distinct periods: 2018-2019 and 2020-2021.
- **Patient-Centric Efficiency Trends:** Provides efficiency trends from a patient-centric perspective, enriching the understanding of individual patient experiences.

3. **Methodological Rigor and Future Research Implications:**

- **Strategic PSC Merging for Data Constraints:** Proposes strategic merging of PSCs to address data limitations, ensuring a comprehensive analysis.
- **Consideration of Euclidean Distance:** Advocates for considering Euclidean distance for transportation methods, aligning with the time-sensitive nature of stroke interventions.
- **Setting the Stage for Future Research:** Proposes future research directions such as telemedicine integration, cost-benefit analysis, community engagement, and environmental impact assessment.
- **Holistic Healthcare Approach:** Advocates for a holistic approach to healthcare improvement, considering broader ecological implications beyond immediate patient care.

These three contributions encompass the geographic efficiency and performance of PSCs, a patient-centric focus with individualized analysis, and methodological rigor with implications for future research and holistic healthcare improvement.

References

1. Adamson J, Beswick A, Ebrahim S. Is stroke the most common cause of disability? Journal of Stroke and Cerebrovascular Diseases. 2004 Jul 1;13(4):171-7.

2. Government of Canada. Stroke in Canada: highlights Canadian chronic disease surveillance system. 2019.

3. Kamal N, Lindsay MP, Côté R, Fang J, Kapral MK, Hill MD. Ten-year trends in stroke admissions and outcomes in Canada. Canadian Journal of Neurological Sciences. 2015 May;42(3):168-75.

4. Kissela BM, Khoury JC, Alwell K, Moomaw CJ, Woo D, Adeoye O, Flaherty ML, Khatri P, Ferioli S, La Rosa FD, Broderick JP. Age at a stroke: temporal trends in stroke incidence in a large, biracial population. Neurology. 2012 Oct 23;79(17):1781-7.

5. The National Institute of Neurological Disorders and Stroke RT-PA stroke study Group. Tissue plasminogen activator for acute ischemic stroke. N Engl J Med. 1995;333(24):1581-7.

6. Goyal M, Menon BK, Van Zwam WH, Dippel DW, Mitchell PJ, Demchuk AM, Dávalos A, Majoie CB, van der Lugt A, De Miquel MA, Donnan GA, et al. Endovascular thrombectomy after large-vessel ischemic stroke: a meta-analysis of individual patient data from five randomized trials. The Lancet. 2016 Apr 23;387(10029):1723-31.

7. Goyal M, Demchuk AM, Menon BK, Eesa M, Rempel JL, Thornton J, Roy D, Jovin TG, Willinsky RA, Sapkota BL, Dowlatshahi D, et al. Randomized assessment of rapid endovascular treatment of ischemic stroke. New England Journal of Medicine. 2015 Mar 12;372(11):1019-30.

8. Papanagiotou P, Ntaios G. Endovascular thrombectomy in acute ischemic stroke. Circulation: Cardiovascular Interventions. 2018 Jan;11(1):e005362.

9. Malhotra K, Gornbein J, Saver JL. Ischemic strokes due to large-vessel occlusions contribute disproportionately to stroke-related dependence and death: a review. Frontiers in neurology. 2017 Nov 30; 8:651.

10. Goyal M, Menon BK, van Zwam WH, Dippel DW, Mitchell PJ, Demchuk AM, Dávalos A, Majoie CB, van der Lugt A, De Miquel MA, Donnan GA. Endovascular thrombectomy after large-vessel ischemic stroke: a meta-analysis of individual patient data from five randomized trials. The Lancet. 2016 Apr 23;387(10029):1723-31.

11. Saver JL. Time is brain qualified. Stroke. 2006 Jan 1;37(1):263-6.

12. Emberson J, Lees KR, Lyden P, Blackwell L, Albers G, Bluhmki E, Brott T, Cohen G, Davis S, Donnan G, Grotta J. Effect of treatment delay, age, and stroke severity on the effects of intravenous thrombolysis with alteplase for acute ischaemic stroke: a meta-analysis of individual patient data from randomized trials. The Lancet. 2014 Nov 29;384(9958):1929-35.

13. Saver JL, Goyal M, Van der Lugt AA, Menon BK, Majoie CB, Dippel DW, Campbell BC, Nogueira RG, Demchuk AM, Tomasello A, Cardona P. Time to treatment with endovascular thrombectomy and outcomes from ischemic stroke: a meta-analysis. Jama. 2016 Sep 27;316(12):1279-89.

14. Demchuk AM, Goyal M, Menon BK, Eesa M, Ryckborst KJ, Kamal N, Patil S, Mishra S, Almekhlafi M, Randhawa PA, Roy D, et al. Endovascular treatment for Small Core and Anterior circulation Proximal occlusion with Emphasis on minimizing CT to recanalization times (ESCAPE) trial: methodology. International Journal of Stroke. 2015 Apr;10(3):429-38.

15. Vagal A, Aviv R, Sucharew H, Reddy M, Hou Q, Michel P, Jovin T, Tomsick T, Wintermark M, Khatri P. Collateral clock is more important than time clock for tissue fate: a natural history study of acute ischemic strokes. Stroke. 2018 Sep;49(9):2102-7.

16. Gao MM, Wang JZ, Liao J, Reiter SD, Vyas MV, Linkewich E, Swartz RH, da Costa L, Kassardjian CD, Amy YX. Delayed Thrombectomy Center Arrival is Associated with Decreased Treatment Probability. Canadian Journal of Neurological Sciences. 2020 Nov;47(6):770-4.

17. Regenhardt RW, Mecca AP, Flavin SA, Boulouis G, Lauer A, Zachrison KS, Boomhower J, Patel AB, Hirsch JA, Schwamm LH, Leslie-Mazwi TM. Delays in the air or ground transfer of patients for endovascular thrombectomy. Stroke. 2018 Jun;49(6):1419-25.

18. Nogueira RG, Jadhav AP, Haussen DC, Bonafe A, Budzik RF, Bhuva P, Yavagal DR, Ribo M, Cognard C, Hanel RA, Sila CA, et al. Thrombectomy 6 to 24 hours after stroke with a mismatch between deficit and infarct. New England Journal of Medicine. 2018 Jan 4;378(1):11-21.

19. Albers GW, Marks MP, Kemp S, Christensen S, Tsai JP, Ortega-Gutierrez S, McTaggart RA, Torbey MT, Kim-Tenser M, Leslie-Mazwi T, Sarraj A, et al. Thrombectomy for stroke at 6 to 16 hours with selection by perfusion imaging. New England Journal of Medicine. 2018 Feb 22;378(8):708-18.

20. McTaggart RA, Moldovan K, Oliver LA, Dibiasio EL, Baird GL, Hemendinger ML, Haas RA, Goyal M, Wang TY, Jayaraman MV. Door-in-door-out time at primary stroke centers may predict outcomes for large emergent vessel occlusion patients. Stroke. 2018 Dec;49(12):2969-74.

21. Choi PM, Tsoi AH, Pope AL, Leung S, Frost T, Loh PS, Chandra RV, Ma H, Parsons M, Mitchell P, Dewey HM. Door-in-door-out time of 60 minutes for stroke with emergent large vessel occlusion at a primary stroke center. Stroke. 2019 Oct;50(10):2829-34.

22. Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision-making units. European journal of operational re-search. 1978 Nov 1;2(6):429-44.

23. Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management science. 1984 Sep;30(9):1078-92.

24. Banker RD, Chang H, Cooper WW. Chapter 11 Simulation studies of efficiency, returns to scale and misspecification with nonlinear functions in DEA. Annals of Operations Research. 1996 Aug; 66:231-53.

25. Grifell-Tatjé E, Lovell CK. A note on the Malmquist productivity index. Economics letters. 1995 Feb 1;47(2):169-75.

26. Andersen P, Petersen NC. A procedure for ranking efficient units in data envelopment analysis. Management science. 1993 Oct;39(10):1261-4.

27. Mirmozaffari M, Kamal N. The Application of Data Envelopment Analysis to Emergency Departments and Management of Emergency Conditions: A Narrative Review. In Healthcare 2023 Sep 14 (Vol. 11, No. 18, p. 2541). MDPI.

28. Alharthi S, Al-Moteri M, Plummer V, Al Thobiaty A. The impact of COVID-19 on the service of emergency department. In-Healthcare 2021 Sep 29 (Vol. 9, No. 10, p. 1295). MDPI.

29. Varner C. Emergency departments are in crisis now and for the foreseeable future. CMAJ. 2023 Jun 19;195(24): E851-2.

30. Kamal N, Benavente O, Boyle K, Buck B, Butcher K, Casaubon LK, Côté R, Demchuk AM, Deschaintre Y, Dowlatshahi D, Gubitz GJ. Good is not good enough: the benchmark stroke door-to-needle time should be 30 minutes. Canadian Journal of Neurological Sciences. 2014 Nov;41(6):694-6.

31. Krumholz HM, Bradley EH, Nallamothu BK, Ting HH, Batchelor WB, Kline-Rogers E, Stern AF, Byrd JR, Brush JE. A campaign to improve the timeliness of primary percutaneous coronary intervention: Door-to-Balloon: An Alliance for Quality. JACC: Cardiovascular Interventions. 2008 Feb;1(1):97-104.

32. Simoons ML, Serruys PW, van den Brand M, Verheugt FW, Krauss XH, Remme WJ, Bär F, de Zwaan C, van der Laarse A, Vermeer F, Lubsen J. Early thrombolysis in acute myocardial infarction: limitation of infarct size and improved survival. Journal of the American College of Cardiology. 1986 Apr 1;7(4):717-28.

33. Reed GW, Rossi JE, Cannon CP. Acute myocardial infarction. The Lancet. 2017 Jan 14;389(10065):197-210.

34. White HD, Chew DP. Acute myocardial infarction. The Lancet. 2008 Aug 16;372(9638):570-84.

35. Anderson JL, Morrow DA. Acute myocardial infarction. New England Journal of Medicine. 2017 May 25;376(21):2053-64.

36. Boersma E, Mercado N, Poldermans D, Gardien M, Vos J, Simoons ML. Acute myocardial infarction. The Lancet. 2003 Mar 8;361(9360):847-58.

37. Mirmozaffari M, Shadkam E, Khalili SM, Kabirifar K, Yazdani R, Asgari Gashteroodkhani T. A novel artificial intelligent approach: Comparison of machine learning tools and algorithms based on optimization DEA Malmquist productivity index for eco-efficiency evaluation. International journal of energy sector management. 2021 May 12;15(3):523-50.

38. Hao S, Pegels CC. Evaluating relative efficiencies of veteran's affairs medical centers using data envelopment, ratio, and multiple regression analysis. Journal of Medical Systems. 1994 Apr; 18:55-67.

39. Butler TW, Li L. The utility of returns to scale in DEA programming: An analysis of Michigan rural hospitals. European Journal of Operational Research. 2005 Mar 1;161(2):469-77.

40. Nayar P, Ozcan YA. Data envelopment analysis comparison of hospital efficiency and quality. Journal of medical systems. 2008 Jun; 32:193-9.

41. Cao F, Xi Y, Zheng C, Bai T, Sun Q. How Efficient are Basic Public Health Services Between Urban and Rural in Shandong Province, China? A Data Envelopment Analysis and Panel Tobit Regression Approach. Risk Management and Healthcare Policy. 2022 Apr 19:727-38.

42. Hassan NZ, Bahari MS, Aminuddin F, Sham MS, Zaimi NA, Hanafiah AN, Kamarudin F. Data envelopment analysis for ambulance services of different service providers in urban and rural areas in Ministry of Health Malaysia. Frontiers in Public Health. 2022;10.

43. Raith A, Ehrgott M, Fauzi F, Lin KM, Macann A, Rouse P, Simpson J. Integrating Data Envelopment Analysis into radiotherapy treatment planning for head and neck cancer patients. European Journal of Operational Research. 2022 Jan 1;296(1):289-303.

44. Akkan C, Karadayi MA, Ekinci Y, Ülengin F, Uray N, Karaosmanoğlu E. Efficiency analysis of emergency departments in metropolitan areas. Socio-Economic Planning Sciences. 2020 Mar 1; 69:100679.

45. Al-Refaie A, Fouad RH, Li MH, Shurrab M. Applying simulation and DEA to improve performance of emergency department in a Jordanian hospital. Simulation Modelling Practice and Theory. 2014 Feb 1; 41:59-72.

46. Chu J, Li X, Yuan Z. Emergency medical resource allocation among hospitals with non-regressive production technology: A DEA-based approach. Computers & Industrial Engineering. 2022 Sep 1; 171:108491.

47. Omrane NA, Manai A, Layeb SB, Siala JC, Hamouda C. Data Envelopment Analysis for Care Production Efficiency Measurement in Ambulatory Care Departments. In 2019 International Conference on Advanced Systems and Emergent Technolo-gies (IC_ASET) 2019 Mar 19 (pp. 102-107). IEEE.

48. Ketabi S, Teymouri E, Ketabi M. Efficiency measurement of emergency departments in Isfahan, Iran. International Journal of Process Management and Benchmarking. 2018;8(2):142-55.

49. Taghipour F, Hamid M, Aghakarimi E, Rabbani M. An integrated framework to evaluate and improve the performance of emergency departments during the COVID-19 pandemic: A mathematical programing approach. Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine. 2023 May 2:09544119231170303.

50. Charnes A, Cooper WW, Golany B, Seiford L, Stutz J. Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. Journal of Econometrics. 1985 Oct 1;30(1-2):91-107.

51. Tone K. A slacks-based measure of efficiency in data envelopment analysis. European journal of operational research. 2001 May 1;130(3):498-509.

52. Liu W, Xia Y, Hou J. Health expenditure efficiency in rural China using the super-SBM model and the Malmquist productivity index. International journal for equity in health. 2019 Dec;18:1-3.

53. Du J, Wang J, Chen Y, Chou SY, Zhu J. Incorporating health outcomes in Pennsylvania hospital efficiency: an additive super-efficiency DEA approach. Annals of Operations Research. 2014 Oct; 221:161-72.

54. Dexter F, O'Neill L, Xin L, Ledolter J. Sensitivity of super-efficient data envelopment analysis results to individual decision-making units: an example of surgical workload by specialty. Health Care Management Science. 2008 Dec; 11:307-18.

55. Fiallos J, Patrick J, Michalowski W, Farion K. Using data envelopment analysis for assessing the performance of pediatric emergency department physicians. Health care management science. 2017 Mar; 20:129-40.

56. Agovino M, Musella G, Scaletti A. Equilibrium and efficiency in the first aid services market: The case of the emergency department of Sorrento. Socio-Economic Planning Sciences. 2022 Aug 1; 82:101313.

57. Bozdemir MK, Avcı S, Aladağ Z. Assessment of the Turkish Health Transformation Program with Data Envelopment Analysis. IEEE Transactions on Engineering Management. 2021 Sep 17.

58. Ngee-Wen T, Zailani S, Aziz AA, Ahmad R. Lean Public Emergency Department Efficiency Evaluation by Slack-based Measure Data Envelopment Analysis. Malaysian Journal of Medicine & Health Sciences. 2020 May 1;16(2).

59. Azadeh A, Ahvazi MP, Haghighii SM, Keramati A. Simulation optimization of an emergency department by modeling human errors. Simulation Modelling Practice and Theory. 2016 Sep 1; 67:117-36.

60. Malmquist S. Index numbers and indifference surfaces. Trabajos de estadística. 1953 Jun;4(2):209-42.

61. Charnes A, Clark CT, Cooper WW, Golany B. A developmental study of data envelopment analysis in measuring the efficiency of maintenance units in the US air forces. Texas Univ at Austin Center for Cybernetic Studies; 1983 Aug 1.

62. Trakakis A, Nektarios M, Tziaferi S, Prezerakos P. Total productivity change of Health Centers in Greece in 2016–2018: a Malmquist index data envelopment analysis application for the primary health system of Greece. Cost Effectiveness and Re-source Allocation. 2021 Dec; 19:1-1.

63. Bağcı H, Çil Koçyiğit S. Evaluating the decentralization of public hospitals in Turkey in terms of technical efficiency: data envelopment analysis and Malmquist index. Benchmarking: An International Journal. 2023 Jan 13.

64. Zhou J, Peng R, Chang Y, Liu Z, Gao S, Zhao C, Li Y, Feng Q, Qin X. Analyzing the efficiency of Chinese primary healthcare institutions using the Malmquist-DEA approach: Evidence from urban and rural areas. Frontiers in Public Health. 2023;11.

65. Jia T, Yuan H. The application of DEA (Data Envelopment Analysis) window analysis in the assessment of influence on oper-ational efficiencies after the establishment of branched hospitals. BMC health services research. 2017 Dec; 17:1-8.

66. Mohd Hassan NZ, Bahari MS, Aminuddin F, Mohd Nor Sham Kunusagaran MS, Zaimi NA, Mohd Hanafiah AN, Kamarudin F. Data envelopment analysis for ambulance services of different service providers in urban and rural areas in Ministry of Health Malaysia. Frontiers in Public Health. 2023 Jan 6; 10:959812.

67. Alinezhad A, Khalili J. EVAMIX method. New methods and applications in multiple attribute decision making (MADM). 2019:59-65.

68. Hassoun MH. Fundamentals of artificial neural networks. MIT press; 1995.

69. Peng CY, Lee KL, Ingersoll GM. An introduction to logistic regression analysis and reporting. The journal of educational re-search. 2002 Sep 1;96(1):3-14.

70. Günal MM, Pidd M. Discrete event simulation for performance modelling in health care: a review of the literature. Journal of Simulation. 2010 Mar 1; 4:42-51.

71. Nayar P, Ozcan YA. Data envelopment analysis comparison of hospital efficiency and quality. Journal of medical systems. 2008 Jun; 32:193-9.

72. Misiunas N, Oztekin A, Chen Y, Chandra K. DEANN: A healthcare analytic methodology of data envelopment analysis and artificial neural networks for the prediction of organ recipient functional status. Omega. 2016 Jan 1; 58:46-54.

73. Khushalani J, Ozcan YA. Are hospitals producing quality care efficiently? An analysis using Dynamic Network Data Envel-opment Analysis (DEA). Socio-Economic Planning Sciences. 2017 Dec 1; 60:15-23.

74. Revuelta I, Santos-Arteaga FJ, Montagud-Marrahi E, Ventura-Aguiar P, Di Caprio D, Cofan F, Cucchiari D, Torregrosa V, Piñeiro GJ, Esforzado N, Bodro M. A hybrid data envelopment analysis—artificial neural network prediction model for COVID-19 severity in transplant recipients. Artificial Intelligence Review. 2021 Aug;54(6):4653-84.

75. Kao LJ, Lu CJ, Chiu CC. Efficiency measurement using independent component analysis and data envelopment analysis. European Journal of Operational Research. 2011 Apr 16;210(2):310-7.

76. Mitropoulos P, Talias MA, Mitropoulos I. Combining stochastic DEA with Bayesian analysis to obtain statistical properties of the efficiency scores: An application to Greek public hospitals. European Journal of Operational Research. 2015 May 16;243(1):302-11.

77. Choukolaei HA, Ghasemi P, Goodarzian F. Evaluating the efficiency of relief centers in disaster and epidemic conditions using multi-criteria decision-making methods and GIS: A case study. International Journal of Disaster Risk Reduction. 2023 Feb 1; 85:103512.

78. Taleb M, Khalid R, Ramli R, Nawawi MK. An integrated approach of discrete event simulation and a non-radial super efficiency data envelopment analysis for performance evaluation of an emergency department. Expert Systems with Applications. 2023 Jun 15; 220:119653.

79. Hajiagha SH, Amoozad Mahdiraji H, Hashemi SS, Garza-Reyes JA, Joshi R. Public Hospitals Performance Measurement through a Three-Staged Data Envelopment Analysis Approach: Evidence from an Emerging Economy. Cybernetics and Systems. 2023 Jan 2;54(1):1-26.

80. Kang H, DeFlitch C. Identifying emergency department efficiency frontiers and the factors associated with their efficiency performance. In IIE Annual Conference. Proceedings 2014 (p. 3974). Institute of Industrial and Systems Engineers (IISE).

81. Weng SJ, Tsai BS, Wang LM, Chang CY, Gotcher D. Using simulation and data envelopment analysis in optimal healthcare efficiency allocations. In Proceedings of the 2011 winter simulation conference (WSC) 2011 Dec 11 (pp. 1295-1305). IEEE.

82. Aminuddin WM, Ismail WR, Husyairi H. Estimating emergency department maximum capacity using simulation and data envelopment analysis. Indian Journal of Sciences & Technology. 2016 Jul;9(28):1-0.

83. Keshtkar L, Rashwan W, Abo-Hamad W, Arisha A. A hybrid system dynamic, discrete event simulation and data envelopment analysis to investigate boarding patients in acute hospitals. Operations Research for Health Care. 2020 Sep 1; 26:100266.

84. Yusoff NS, Liong CY, Noh AM, Ismail WR. Discrete event simulation and data envelopment analysis models for selecting the best resource allocation alternative at an emergency department's Green Zone. Sains Malaysiana. 2018 Nov 1;47(11):2917-25.

85. Nazari-Shirkouhi S, Yaghoubi A, Taghizadeh Yazdi MR. Discrete Event Simulation and Data Envelopment Analysis to Improve the Performance of Hospital Emergency Department. Industrial Management Journal. 2019 May 22;11(1):63-82.

86. Ismail K, Thorwarth M, Arisha A. Integrated decision support systems for improving emergency department performance in Irish hospitals. International Journal of Operational Research. 2014 Jan 1;19(1):40-59.

87. Rabbani M, Farshbaf-Geranmayeh A, Yazdanparast R. A simulation optimization approach for integrated resource allocation in an emergency department, pharmacy, and lab. Intelligent Decision Technologies. 2018 Jan 1;12(2):187-212.

88. Yazdanparast R, Hamid M, Azadeh MA, Keramati A. An intelligent algorithm for optimization of resource allocation problem by considering human error in an emergency department. Journal of Industrial and Systems Engineering. 2018 Sep 14;11(1):287-309.

89. Kang H, Nembhard H, DeFlitch C, Pasupathy K. Assessment of emergency department efficiency using data envelopment analysis. IISE transactions on healthcare systems engineering. 2017 Oct 2;7(4):236-46.

90. Labijak-Kowalska A, Kadziński M, Spychała I, Dias LC, Fiallos J, Patrick J, Michalowski W, Farion K. Performance evaluation of emergency department physicians using robust value-based additive efficiency model. International Transactions in Operational Research. 2023 Jan;30(1):503-44.

91. Antunes J, Hadi-Vencheh A, Jamshidi A, Tan Y, Wanke P. TEA-IS: A hybrid DEA-TOPSIS approach for assessing performance and synergy in Chinese health care. Decision Support Systems. 2023 Jan 4:113916.

92. Ward MJ, Farley H, Khare RK, Kulstad E, Mutter RL, Shesser R, Stone-Griffith S. Achieving efficiency in crowded emergency departments: a research agenda. Academic Emergency Medicine. 2011 Dec;18(12):1303-12.

93. Abdel-Basset M, Gamal A, Mohamed R, Abouhawwash M, Almutairi A, ELkomy OM. Efficient Model for Emergency Departments: Real Case Study. Computers, Materials & Continua. 2022 Feb 1;70(2).

94. Gharahighehi A, Kheirkhah AS, Bagheri A, Rashidi E. Improving performances of the emergency department using discrete event simulation, DEA and the MADM methods. Digital health. 2016 Aug; 2:2055207616664619.

95. Ozcan YA, Watts J, Harris JM, Wogen SE. Provider experience and technical efficiency in the treatment of stroke patients: DEA approach. Journal of the Operational Research Society. 1998 Jun 1;49(6):573-82.

96. Behr A, Theune K. Health system efficiency: a fragmented picture based on OECD data. Pharmaco Economics-open. 2017 Sep; 1:203-21.

97. Amiri A. Nursing Graduates and Quality of Acute Hospital Care in 33 OECD Countries: Evidence from Generalized Linear Models and Data Envelopment Analysis. SAGE Open Nursing. 2021 Mar; 7:23779608211005217.

98. Koltai T, Dénes RV, Dénes Z. Analysis of the effect of patients' health status on efficiency: Application of data envelopment analysis in healthcare. Health Services Management Research. 2023 Feb;36(1):2-9.

99. Mirmozaffari M, Shadkam E, Khalili SM, Yazdani M. Developing a novel integrated generalised data envelopment analysis (DEA) to evaluate hospitals providing stroke care services. Bioengineering. 2021 Dec 10;8(12):207.

100. Peykani P, Memar-Masjed E, Arabjazi N, Mirmozaffari M. Dynamic performance assessment of hospitals by applying credi-bility-based fuzzy window data envelopment analysis. In Healthcare 2022 May 9 (Vol. 10, No. 5, p. 876). MDPI.

101. Mirmozaffari M, Alinezhad A. Window analysis using two-stage DEA in heart hospitals. In10th International Conference on Innovations in Science, Engineering, Computers and Technology (ISECT-2017) 2017 Oct 17 (pp. 44-51).

102. Chiu CM, Chen MS, Lin CS, Lin WY, Lang HC. Evaluating the comparative efficiency of medical centers in Taiwan: A dynamic data envelopment analysis application. BMC Health Services Research. 2022 Dec;22(1):1-1.

103. Miller F, Wang J, Zhu J, Chen Y, Hockenberry J. Investigation of the impact of the Massachusetts health care reform on hospital costs and quality of care. Annals of Operations Research. 2017 Mar; 250:129-46.

104. Ortíz-Barrios M, Jaramillo-Rueda N, Gul M, Yucesan M, Jiménez-Delgado G, Alfaro-Saíz JJ. A Fuzzy Hybrid MCDM Approach for Assessing the Emergency Department Performance during the COVID-19 Outbreak. International Journal of Environmental Research and Public Health. 2023 Mar 5;20(5):4591.

105. Memarpour Ghiaci A, Garg H, Jafarzadeh Ghoushchi S. Improving emergency departments during COVID-19 pandemic: a simulation and MCDM approach with MARCOS methodology in an uncertain environment. Computational and Applied Mathematics. 2022 Dec;41(8):368.

106. Hsieh MC, Wang EM, Lee WC, Li LW, Hsieh CY, Tsai W, Wang CP, Huang JL, Liu TC. Application of HFACS, fuzzy TOPSIS, and AHP for identifying important human error factors in emergency departments in Taiwan. International Journal of Industrial Ergonomics. 2018 Sep 1; 67:171-9.

107. Amarantou V, Chatzoudes D, Angelidis V, Xanthopoulos A, Chatzoglou P. Improving the operations of an emergency department (ED) using a combined approach of simulation and analytical hierarchical process (AHP). Journal of Simulation. 2023 Mar 4;17(2):193-210.

108. Chalgham M, Khatrouch I, Masmoudi M, Walha OC, Dammak A. Inpatient admission management using multiple criteria decision-making methods. Operations Research for Health Care. 2019 Dec 1; 23:100173.

109. Ortiz-Barrios MA, Aleman-Romero BA, Rebolledo-Rudas J, Maldonado-Mestre H, Montes-Villa L, De Felice F, Petrillo A. The analytic decision-making preference model to evaluate the disaster readiness in emergency departments: The ADT model. Journal of Multi-Criteria Decision Analysis. 2017 Sep;24(5-6):204-26.

110. Gul M. Emergency department ergonomic design evaluation: A case study using fuzzy DEMATEL-focused two-stage methodology. Health Policy and Technology. 2019 Dec 1;8(4):365-76.

111. Chang MW, Kung CT, Yu SF, Wang HT, Lin CL. Exploring the Critical Driving Forces and Strategy Adoption Paths of Professional Competency Development for Various Emergency Physicians Based on the Hybrid MCDM Approach. In Healthcare 2023 Feb 6 (Vol. 11, No. 4, p. 471). MDPI.

112. Al-Bayati AR, Nogueira RG, Samaniego EA, Haussen DC. Mechanical Thrombectomy: Techniques and Hybrid Approaches for Recanalization. Acute Stroke Management in the Era of Thrombectomy. 2019:87-103.

113. Boussofiane A, Dyson RG, Thanassoulis E. Applied data envelopment analysis. European journal of operational research. 1991 May 6;52(1):1-5.

114. Färe R, Lovell CK. Measuring the technical efficiency of production. Journal of Economic theory. 1978 Oct 1;19(1):150-62.

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Appendix B: Study 2 Supplementary

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

DMUs	Category	Original	Target	Radial	Non-radial
1	DIDI Time (Door-In-Door-In)	0.807957154	0.147523055	-0.50862627	-0.151807829
	Driving Distance	0.3925	0.145412874	-0.247087126	0
	Euclidean Distance	0.408119521	0.149670629	-0.256919948	-0.001528944
	Onset_to_1st_CT	0.101744186	0.03769405	-0.064050136	0
	Onset_To_Arrival_1st	0.15942029	0.048331173	-0.100358475	-0.010730642
2	DIDI Time (Door-In-Door-In)	0.204284621	0.109255466	-0.095029155	0
	Driving Distance	0.5425	0.273932476	-0.252360242	-0.016207282
	Euclidean Distance	0.533943311	0.285563471	-0.24837984	4.16E-10
	Onset_to_1st_CT	0.04244186	0.022698748	-0.019743112	0
	Onset_To_Arrival_1st	0.057971014	0.031004048	-0.026966966	0
3	DIDI Time (Door-In-Door-In)	0.176740627	0.099072459	-0.077668168	6.66E-10
	Driving Distance	0.755	0.339469904	-0.331782613	-0.083747482
	Euclidean Distance	0.70925843	0.353053119	-0.31168161	-0.044523701
	Onset_to_1st_CT	0.046511628	0.026072225	-0.020439403	0
	Onset_To_Arrival_1st	0.072463768	0.04061977	-0.031843998	2.64E-10
4	DIDI Time (Door-In-Door-In)	0.094108646	0.093515002	-0.000593644	1.12E-10
	Driving Distance	0.3925	0.31221161	-0.002475917	-0.077812473
	Euclidean Distance	0.408119521	0.324700019	-0.002574447	-0.080845056
	Onset_to_1st_CT	0.038372093	0.038130039	-0.000242054	-1.25E-10
	Onset_To_Arrival_1st	0.050724638	0.050404663	-0.000319975	-1.47E-10
5	DIDI Time (Door-In-Door-In)	0.257077276	0.115389132	-0.141688143	-9.58E-10
	Driving Distance	0.8975	0.272729317	-0.494657134	-0.130113549
	Euclidean Distance	0.800531064	0.282130006	-0.441212704	-0.077188354
	Onset_to_1st_CT	0.039534884	0.017745232	-0.021789652	-1.36E-10
	Onset_To_Arrival_1st	0.049818841	0.022361186	-0.027457655	-2.96E-10
6	DIDI Time (Door-In-Door-In)	0.179801071	0.08838908	-0.091411992	8.49E-10
	Driving Distance	0.755	0.243531398	-0.383846734	-0.127621868
	Euclidean Distance	0.70925843	0.258557957	-0.360591433	-0.090109041
	Onset_to_1st_CT	0.091860465	0.045158029	-0.046702436	3.71E-10
	Onset_To_Arrival_1st	0.13134058	0.062693125	-0.066774374	-0.001873081

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

7	DIDI Time (Door-In-Door-In)	0.123182862	0.090613052	-0.032569811	1.06E-09
	Driving Distance	0.3925	0.252919665	-0.103777836	-0.035802499
	Euclidean Distance	0.408119521	0.269192801	-0.107907671	-0.031019049
	Onset_to_1st_CT	0.05755814	0.042339646	-0.015218495	5.15E-10
	Onset_To_Arrival_1st	0.079710145	0.058634614	-0.021075532	7.02E-10
8	DIDI Time (Door-In-Door-In)	1	0.143075746	0	-0.856924254
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.04244186	0.038953488	0	-0.003488372
	Onset_To_Arrival_1st	0.048007246	0.000905797	0	-0.047101449
9	DIDI Time (Door-In-Door-In)	0.148431523	0.104800487	-0.043631037	8.45E-10
	Driving Distance	0.23175	0.163627728	-0.068122273	9.05E-10
	Euclidean Distance	0.260733252	0.169884618	-0.07664182	-0.014206814
	Onset_to_1st_CT	0.045930233	0.032429167	-0.013501065	-4.15E-10
	Onset_To_Arrival_1st	0.070652174	0.049884162	-0.020768012	-4.92E-10
10	DIDI Time (Door-In-Door-In)	0.355011477	0.073312291	-0.281699186	0
	Driving Distance	1	0.145621203	-0.79349318	-0.060885617
	Euclidean Distance	1	0.149901822	-0.79349318	-0.056604998
	Onset_to_1st_CT	0.31744186	0.065553909	-0.251887951	1.74E-10
	Onset_To_Arrival_1st	0.454710145	0.093900746	-0.360809399	1.77E-10
11	DIDI Time (Door-In-Door-In)	0.321346595	0.143075746	0	-0.178270849
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.362209302	0.038953488	0	-0.323255814
	Onset_To_Arrival_1st	0.428442029	0.000905797	0	-0.427536232
12	DIDI Time (Door-In-Door-In)	0.100994644	0.088261544	-0.012733101	3.53E-10
	Driving Distance	0.2625	0.229404791	-0.03309521	1.13E-09
	Euclidean Distance	0.27960842	0.243188607	-0.035252188	-0.001167625
	Onset_to_1st_CT	0.056976744	0.049793287	-0.007183456	-5.14E-10
	Onset_To_Arrival_1st	0.077898551	0.068077336	-0.009821215	-4.03E-10
13	DIDI Time (Door-In-Door-In)	0.224942617	0.117476364	-0.107466252	-5.00E-10
	Driving Distance	0.3925	0.142845955	-0.18751673	-0.062137315
	Euclidean Distance	0.408119521	0.14693075	-0.19497895	-0.066209821
	Onset_to_1st_CT	0.074418605	0.038865144	-0.035553461	-1.34E-10
	Onset_To_Arrival_1st	0.054347826	0.028383172	-0.025964654	0

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

14	DIDI Time (Door-In-Door-In)	0.116296863	0.116296863	0	-4.37E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.097093023	0.059431936	0	-0.037661087
	Onset_To_Arrival_1st	0.125	0.036041494	0	-0.088958506
15	DIDI Time (Door-In-Door-In)	0.631981637	0.161404021	-0.458231513	-0.012346102
	Driving Distance	0.3925	0.106066279	-0.28459034	-0.001843381
	Euclidean Distance	0.408119521	0.112203917	-0.295915601	-3.00E-09
	Onset_to_1st_CT	0.538953488	0.086524872	-0.390779507	-0.061649109
	Onset_To_Arrival_1st	0.222826087	0.061261367	-0.161564718	-1.38E-09
16	DIDI Time (Door-In-Door-In)	0.140015302	0.140015302	0	-1.53E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.103488372	0.041293882	0	-0.06219449
	Onset_To_Arrival_1st	0.124094203	0.004921305	0	-0.119172898
17	DIDI Time (Door-In-Door-In)	0.207345065	0.143075746	0	-0.064269319
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.587790698	0.038953488	0	-0.54883721
	Onset_To_Arrival_1st	0.808876812	0.000905797	0	-0.807971015
18	DIDI Time (Door-In-Door-In)	0.143075746	0.143075746	0	0
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.038953488	0.038953488	0	0
	Onset_To_Arrival_1st	0.000905797	0.000905797	0	0
19	DIDI Time (Door-In-Door-In)	0.10558531	0.10558531	0	0
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.233139535	0.067623315	0	-0.16551622
	Onset_To_Arrival_1st	0.22192029	0.050095772	0	-0.171824518
20	DIDI Time (Door-In-Door-In)	0.022953328	0.022953328	0	0
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.130813953	0.130813953	0	0
	Onset_To_Arrival_1st	0.158514493	0.158514493	0	0
21	DIDI Time (Door-In-Door-In)	0.301453711	0.143075746	0	-0.158377965
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.294186047	0.038953488	0	-0.255232559
	Onset_To_Arrival_1st	0.237318841	0.000905797	0	-0.236413044

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

22	DIDI Time (Door-In-Door-In)	0.139250191	0.139250191	0	0
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.026744186	0.026744186	0	0
	Onset_To_Arrival_1st	0.000905797	0.000905797	0	0
23	DIDI Time (Door-In-Door-In)	0.434583015	0.143075746	0	-0.291507269
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.263372093	0.038953488	0	-0.224418605
	Onset_To_Arrival_1st	0.000905797	0.000905797	0	0
24	DIDI Time (Door-In-Door-In)	0.311400153	0.311400153	0	0
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.116860465	0.116860465	0	0
	Onset_To_Arrival_1st	0.038949275	0.038949275	0	0
25	DIDI Time (Door-In-Door-In)	0.413925019	0.143075746	0	-0.270849273
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.30872093	0.038953488	0	-0.269767442
	Onset_To_Arrival_1st	0.382246377	0.000905797	0	-0.38134058
26	DIDI Time (Door-In-Door-In)	0.092578424	0.092578424	0	0
	Driving Distance	0.2625	0.2625	0	0
	Euclidean Distance	0.27960842	0.27960842	0	0
	Onset_to_1st_CT	0.037790698	0.037790698	0	0
	Onset_To_Arrival_1st	0.055253623	0.055253623	0	0
27	DIDI Time (Door-In-Door-In)	0.299923489	0.098278238	-0.20164525	-6.74E-10
	Driving Distance	0.5425	0.168202347	-0.364734848	-0.009562805
	Euclidean Distance	0.533943311	0.174961316	-0.358981995	-5.14E-10
	Onset_to_1st_CT	0.151744186	0.049723186	-0.102021	-3.10E-10
	Onset_To_Arrival_1st	0.208333333	0.053196599	-0.140067146	-0.015069588
28	DIDI Time (Door-In-Door-In)	0.197398623	0.130681169	-0.066717454	0
	Driving Distance	1	0.31566126	-0.33798338	-0.34635536
	Euclidean Distance	1	0.313594333	-0.33798338	-0.348422287
	Onset_to_1st_CT	0.037790698	0.02501807	-0.012772628	0
	Onset_To_Arrival_1st	0.055253623	0.036578817	-0.018674806	0
29	DIDI Time (Door-In-Door-In)	0.167559296	0.167559295	0	-8.09E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.087790698	0.050285412	0	-0.037505286
	Onset_To_Arrival_1st	0.059782609	0.006439394	0	-0.053343215

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

30	DIDI Time (Door-In-Door-In)	0.302983933	0.143075746	0	-0.159908187
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.145930233	0.038953488	0	-0.106976745
	Onset_To_Arrival_1st	0.072463768	0.000905797	0	-0.071557971
31	DIDI Time (Door-In-Door-In)	0.205049732	0.152423479	-0.032135326	-0.020490927
	Driving Distance	0.755	0.627374264	-0.118323351	-0.009302385
	Euclidean Distance	0.70925843	0.598103679	-0.111154747	-3.68E-09
	Onset_to_1st_CT	0.023255814	0.01961117	-0.003644643	-1.60E-10
	Onset_To_Arrival_1st	0.030797101	0.025970589	-0.004826512	-2.92E-10
32	DIDI Time (Door-In-Door-In)	0.13006886	0.054191226	-0.075877635	8.57E-10
	Driving Distance	0.23175	0.09294723	-0.135194864	-0.003607906
	Euclidean Distance	0.260733252	0.091446722	-0.152102682	-0.017183847
	Onset_to_1st_CT	0.223255814	0.093016162	-0.130239652	7.89E-10
	Onset_To_Arrival_1st	0.34692029	0.119971796	-0.202381193	-0.024567301
33	DIDI Time (Door-In-Door-In)	0.355011477	0.073312291	-0.281699186	0
	Driving Distance	1	0.145621203	-0.79349318	-0.060885617
	Euclidean Distance	1	0.149901822	-0.79349318	-0.056604998
	Onset_to_1st_CT	0.31744186	0.065553909	-0.251887951	1.74E-10
	Onset_To_Arrival_1st	0.454710145	0.093900746	-0.360809399	1.77E-10
34	DIDI Time (Door-In-Door-In)	0.547819434	0.143075746	0	-0.404743688
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.159883721	0.038953488	0	-0.120930233
	Onset_To_Arrival_1st	0.136775362	0.000905797	0	-0.135869565
35	DIDI Time (Door-In-Door-In)	0.101759755	0.101759754	0	-7.57E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.549418605	0.122903758	0	-0.426514847
	Onset_To_Arrival_1st	0.843297101	0.147278221	0	-0.69601888
36	DIDI Time (Door-In-Door-In)	0.21117062	0.084727426	-0.126443194	0
	Driving Distance	0.8975	0.180736656	-0.537398462	-0.179364882
	Euclidean Distance	0.800531064	0.188871302	-0.479336115	-0.132323647
	Onset_to_1st_CT	0.128488372	0.051553047	-0.076935324	-5.56E-10
	Onset_To_Arrival_1st	0.194746377	0.07813757	-0.116608806	-6.38E-10

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

37	DIDI Time (Door-In-Door-In)	0.141545524	0.141545525	0	6.27E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.288953488	0.040123685	0	-0.248829803
	Onset_To_Arrival_1st	0.401268116	0.002913551	0	-0.398354565
38	DIDI Time (Door-In-Door-In)	0.166029074	0.098514466	-0.067514607	-6.98E-10
	Driving Distance	0.3925	0.228543369	-0.159607487	-0.004349144
	Euclidean Distance	0.408119521	0.24216046	-0.165959061	-3.79E-10
	Onset_to_1st_CT	0.063953488	0.037947232	-0.026006256	-1.37E-10
	Onset_To_Arrival_1st	0.081521739	0.048371472	-0.033150267	0
39	DIDI Time (Door-In-Door-In)	0.221117062	0.088012448	-0.133104615	8.21E-10
	Driving Distance	0.755	0.241826075	-0.454483175	-0.05869075
	Euclidean Distance	0.70925843	0.256665469	-0.426948375	-0.025644586
	Onset_to_1st_CT	0.115116279	0.045820369	-0.06929591	3.76E-10
	Onset_To_Arrival_1st	0.161231884	0.063361953	-0.097055866	-0.000814065
40	DIDI Time (Door-In-Door-In)	0.118592196	0.103587694	-0.015004503	5.38E-10
	Driving Distance	0.3925	0.321009491	-0.049659822	-0.021830687
	Euclidean Distance	0.408119521	0.337447798	-0.051636033	-0.01903569
	Onset_to_1st_CT	0.022674419	0.01980561	-0.002868809	0
	Onset_To_Arrival_1st	0.043478261	0.037977312	-0.00550095	0
41	DIDI Time (Door-In-Door-In)	0.26013772	0.26013772	0	0
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.1	0.1	0	0
	Onset_To_Arrival_1st	0.139492754	0.139492754	0	0
42	DIDI Time (Door-In-Door-In)	0.126243305	0.112471308	0	-0.013771997
	Driving Distance	0.2625	0.2625	0	0
	Euclidean Distance	0.27960842	0.27960842	0	0
	Onset_to_1st_CT	0.023255814	0.023255814	0	0
	Onset_To_Arrival_1st	0.0625	0.057971014	0	-0.004528986
43	DIDI Time (Door-In-Door-In)	0.359602142	0.142574489	-0.21216621	-0.004861444
	Driving Distance	1	0.409997372	-0.59000263	1.88E-09
	Euclidean Distance	1	0.393152425	-0.59000263	-0.016844945
	Onset_to_1st_CT	0.036627907	0.015017346	-0.021610561	0
	Onset_To_Arrival_1st	0.045289855	0.018568722	-0.026721134	2.13E-10

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

44	**DIDI Time (Door-In-Door-In)**	**0.136954858**	**0.080877641**	**-0.056077217**	**-2.96E-10**
	Driving Distance	**0.5425**	**0.209520943**	**-0.222130786**	**-0.110848271**
	Euclidean Distance	**0.533943311**	**0.220814751**	**-0.218627184**	**-0.094501376**
	Onset_to_1st_CT	**0.098837209**	**0.058367555**	**-0.040469653**	**-2.01E-10**
	Onset_To_Arrival_1st	**0.153985507**	**0.076032052**	**-0.063050547**	**-0.014902908**
45	**DIDI Time (Door-In-Door-In)**	**0.096403979**	**0.096403979**	**0**	**0**
	Driving Distance	**0.23175**	**0.23175**	**0**	**0**
	Euclidean Distance	**0.260733252**	**0.260733252**	**0**	**0**
	Onset_to_1st_CT	**0.108139535**	**0.108139535**	**0**	**0**
	Onset_To_Arrival_1st	**0.04076087**	**0.04076087**	**0**	**0**
46	**DIDI Time (Door-In-Door-In)**	**0.133894415**	**0.082201777**	**-0.051692638**	**3.73E-10**
	Driving Distance	**0.3925**	**0.215516396**	**-0.151532538**	**-0.025451066**
	Euclidean Distance	**0.408119521**	**0.227468224**	**-0.157562769**	**-0.023088528**
	Onset_to_1st_CT	**0.09127907**	**0.056038945**	**-0.035240125**	**0**
	Onset_To_Arrival_1st	**0.122282609**	**0.07368063**	**-0.047209666**	**-0.001392312**
47	**DIDI Time (Door-In-Door-In)**	**0.198163734**	**0.159679399**	**-0.038484334**	**0**
	Driving Distance	**1**	**0.706692588**	**-0.19420473**	**-0.099102682**
	Euclidean Distance	**1**	**0.667270574**	**-0.19420473**	**-0.138524696**
	Onset_to_1st_CT	**0.023837209**	**0.01920791**	**-0.004629299**	**0**
	Onset_To_Arrival_1st	**0.023550725**	**0.018977063**	**-0.004573662**	**0**
48	**DIDI Time (Door-In-Door-In)**	**0.142310635**	**0.105520484**	**-0.036790151**	**1.61E-10**
	Driving Distance	**0.2625**	**0.19463849**	**-0.067861511**	**0**
	Euclidean Distance	**0.27960842**	**0.204298904**	**-0.07228438**	**-0.003025136**
	Onset_to_1st_CT	**0.030813953**	**0.022847928**	**-0.007966024**	**-5.74E-10**
	Onset_To_Arrival_1st	**0.079710145**	**0.04647989**	**-0.02060667**	**-0.012623585**
49	**DIDI Time (Door-In-Door-In)**	**0.451415455**	**0.06605431**	**-0.385361145**	**-1.55E-10**
	Driving Distance	**1**	**0.128432521**	**-0.85367291**	**-0.017894569**
	Euclidean Distance	**1**	**0.138635686**	**-0.85367291**	**-0.007691404**
	Onset_to_1st_CT	**0.820930233**	**0.119600085**	**-0.700805901**	**-0.000524247**
	Onset_To_Arrival_1st	**0.652173913**	**0.09543071**	**-0.556743202**	**-9.58E-10**
50	**DIDI Time (Door-In-Door-In)**	**0.257077276**	**0.137620813**	**-0.112582931**	**-0.006873532**
	Driving Distance	**0.755**	**0.409264771**	**-0.330640321**	**-0.015094909**
	Euclidean Distance	**0.70925843**	**0.398649907**	**-0.310608523**	**-1.13E-10**
	Onset_to_1st_CT	**0.040697674**	**0.022874771**	**-0.017822903**	**0**
	Onset_To_Arrival_1st	**0.058876812**	**0.033092643**	**-0.02578417**	**1.72E-10**

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

51	DIDI Time (Door-In-Door-In)	0.185156848	0.066835863	-0.118320986	1.15E-09
	Driving Distance	0.3925	0.132149409	-0.250819711	-0.00953088
	Euclidean Distance	0.408119521	0.134951459	-0.260801071	-0.012366992
	Onset_to_1st_CT	0.200581395	0.072403644	-0.128177751	5.09E-10
	Onset_To_Arrival_1st	0.307065217	0.101360705	-0.196224226	-0.009480286
52	DIDI Time (Door-In-Door-In)	0.589135425	0.143075746	0	-0.446059679
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.079069767	0.038953488	0	-0.040116279
	Onset_To_Arrival_1st	0.042572464	0.000905797	0	-0.041666667
53	DIDI Time (Door-In-Door-In)	0.213465953	0.130876794	-0.041239462	-0.041349697
	Driving Distance	0.23175	0.186978245	-0.044771755	-3.23E-10
	Euclidean Distance	0.260733252	0.195797925	-0.050371026	-0.014564302
	Onset_to_1st_CT	0.034883721	0.028144539	-0.006739182	0
	Onset_To_Arrival_1st	0.053442029	0.04311757	-0.010324459	0
54	DIDI Time (Door-In-Door-In)	0.52027544	0.091112356	-0.429163083	-1.38E-09
	Driving Distance	0.755	0.122468176	-0.622781901	-0.009749923
	Euclidean Distance	0.70925843	0.124207681	-0.585050746	-2.57E-09
	Onset_to_1st_CT	0.395930233	0.069336612	-0.32659362	-1.38E-09
	Onset_To_Arrival_1st	0.572463768	0.085009878	-0.472212018	-0.015241872
55	DIDI Time (Door-In-Door-In)	0.125478194	0.106468828	-0.019009365	-1.04E-09
	Driving Distance	0.23175	0.196640947	-0.035109052	-9.31E-10
	Euclidean Distance	0.260733252	0.206334397	-0.03949988	-0.014898974
	Onset_to_1st_CT	0.041860465	0.035518798	-0.006341667	-2.49E-10
	Onset_To_Arrival_1st	0.045289855	0.038428651	-0.006861203	-1.97E-10
56	DIDI Time (Door-In-Door-In)	0.177505738	0.11146656	-0.066039178	3.96E-10
	Driving Distance	0.23175	0.145529805	-0.086220196	7.40E-10
	Euclidean Distance	0.260733252	0.149800393	-0.097003116	-0.013929743
	Onset_to_1st_CT	0.046511628	0.029207457	-0.017304171	0
	Onset_To_Arrival_1st	0.06884058	0.040298545	-0.025611427	-0.002930608
57	DIDI Time (Door-In-Door-In)	0.112471308	0.111844904	-0.000626404	0
	Driving Distance	0.2625	0.261038017	-0.001461983	0
	Euclidean Distance	0.27960842	0.276743188	-0.001557268	-0.001307964
	Onset_to_1st_CT	0.00755814	0.007516045	-4.21E-05	0
	Onset_To_Arrival_1st	0.036231884	0.036030092	-0.000201792	0

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

58	DIDI Time (Door-In-Door-In)	0.169089518	0.097529979	-0.07155954	2.64E-10
	Driving Distance	0.2625	0.151408672	-0.111091328	0
	Euclidean Distance	0.27960842	0.156324484	-0.118331698	-0.004952238
	Onset_to_1st_CT	0.073837209	0.042588929	-0.03124828	7.02E-10
	Onset_To_Arrival_1st	0.115036232	0.060984596	-0.048683915	-0.005367721
59	DIDI Time (Door-In-Door-In)	0.136954858	0.098207447	-0.038747412	7.71E-10
	Driving Distance	0.5425	0.225617283	-0.15348467	-0.163398048
	Euclidean Distance	0.533943311	0.238677713	-0.151063802	-0.144201796
	Onset_to_1st_CT	0.03255814	0.023346757	-0.009211383	-1.78E-10
	Onset_To_Arrival_1st	0.153985507	0.056366358	-0.043565741	-0.054053408
60	DIDI Time (Door-In-Door-In)	0.263963275	0.120219007	-0.143744269	6.75E-10
	Driving Distance	0.8975	0.358797544	-0.488744054	-0.049958402
	Euclidean Distance	0.800531064	0.364592573	-0.435938493	1.87E-09
	Onset_to_1st_CT	0.072674419	0.03309872	-0.039575699	3.05E-10
	Onset_To_Arrival_1st	0.10326087	0.047028964	-0.056231907	3.04E-10
61	DIDI Time (Door-In-Door-In)	0.436113236	0.088765915	-0.347347319	-1.30E-09
	Driving Distance	1	0.193953456	-0.79646131	-0.009585234
	Euclidean Distance	1	0.203538686	-0.79646131	-3.55E-09
	Onset_to_1st_CT	0.260465116	0.053014728	-0.207450387	-8.76E-10
	Onset_To_Arrival_1st	0.362318841	0.064644956	-0.288572939	-0.009100947
62	DIDI Time (Door-In-Door-In)	0.343534813	0.126581168	-0.17138879	-0.045564855
	Driving Distance	0.2625	0.131539308	-0.130960694	1.68E-09
	Euclidean Distance	0.27960842	0.134274397	-0.139496048	-0.005837975
	Onset_to_1st_CT	0.03255814	0.016314953	-0.016243187	0
	Onset_To_Arrival_1st	0.055253623	0.017987493	-0.027565915	-0.009700215
63	DIDI Time (Door-In-Door-In)	0.166794185	0.105906099	-0.060888085	-4.25E-10
	Driving Distance	0.23175	0.147149846	-0.084600154	0
	Euclidean Distance	0.260733252	0.151598238	-0.095180468	-0.013954546
	Onset_to_1st_CT	0.054651163	0.034700799	-0.019950364	0
	Onset_To_Arrival_1st	0.081521739	0.048563702	-0.029759446	-0.003198591
64	DIDI Time (Door-In-Door-In)	0.122417751	0.122417751	0	-1.77E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.331395349	0.054751147	0	-0.276644202
	Onset_To_Arrival_1st	0.490942029	0.028010477	0	-0.462931552

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

65	DIDI Time (Door-In-Door-In)	0.206579954	0.125467998	-0.02062642	-0.060485536
	Driving Distance	0.2625	0.236135293	-0.026209877	-0.00015483
	Euclidean Distance	0.27960842	0.251690317	-0.027918104	4.51E-10
	Onset_to_1st_CT	0.04244186	0.038204161	-0.004237699	0
	Onset_To_Arrival_1st	0.071557971	0.064413112	-0.007144859	1.60E-10
66	DIDI Time (Door-In-Door-In)	0.612853864	0.143075746	0	-0.469778118
	Driving Distance	0.3925	0.02	0	-0.3725
	Euclidean Distance	0.408119521	0.010493314	0	-0.397626207
	Onset_to_1st_CT	0.058139535	0.038953488	0	-0.019186047
	Onset_To_Arrival_1st	0.000905797	0.000905797	0	0
67	DIDI Time (Door-In-Door-In)	0.256312165	0.099751315	-0.15656085	2.89E-10
	Driving Distance	0.755	0.257662665	-0.461169847	-0.036167487
	Euclidean Distance	0.70925843	0.276028495	-0.433229936	8.87E-10
	Onset_to_1st_CT	0.106395349	0.041406837	-0.064988512	1.59E-10
	Onset_To_Arrival_1st	0.141304348	0.054992686	-0.086311662	1.73E-10
68	DIDI Time (Door-In-Door-In)	0.244835501	0.043358433	-0.201477068	0
	Driving Distance	0.2625	0.046486677	-0.216013324	6.55E-10
	Euclidean Distance	0.27960842	0.039886984	-0.230091978	-0.009629459
	Onset_to_1st_CT	0.680232558	0.120463811	-0.559768746	-1.10E-09
	Onset_To_Arrival_1st	1	0.139668384	-0.8229079	-0.037423716
69	DIDI Time (Door-In-Door-In)	0.192042846	0.044512883	-0.147529963	-9.09E-10
	Driving Distance	0.23175	0.050748612	-0.178033546	-0.002967842
	Euclidean Distance	0.260733252	0.044616679	-0.20029888	-0.015817693
	Onset_to_1st_CT	0.498255814	0.115488825	-0.382766987	-1.69E-09
	Onset_To_Arrival_1st	0.761775362	0.138010031	-0.585206338	-0.038558993
70	DIDI Time (Door-In-Door-In)	0.255547054	0.11172741	-0.143819643	-4.36E-10
	Driving Distance	0.3925	0.171331073	-0.220895562	-0.000273366
	Euclidean Distance	0.408119521	0.178433428	-0.229686091	-1.75E-09
	Onset_to_1st_CT	0.068604651	0.029994554	-0.038610097	0
	Onset_To_Arrival_1st	0.077898551	0.034057929	-0.043840622	-3.00E-10
71	DIDI Time (Door-In-Door-In)	0.351185922	0.143075746	0	-0.208110176
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.623255814	0.038953488	0	-0.584302326
	Onset_To_Arrival_1st	0.72192029	0.000905797	0	-0.721014493

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

72	DIDI Time (Door-In-Door-In)	0.214996174	0.143075746	0	-0.071920428
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.109883721	0.038953488	0	-0.070930233
	Onset_To_Arrival_1st	0.075181159	0.000905797	0	-0.074275362
73	DIDI Time (Door-In-Door-In)	0.042081102	0.042081102	0	-2.88E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.413372093	0.11618649	0	-0.297185603
	Onset_To_Arrival_1st	0.786231884	0.133417567	0	-0.652814317
74	DIDI Time (Door-In-Door-In)	0.498852334	0.101779964	-0.39707237	0
	Driving Distance	0.2625	0.053557414	-0.208942587	6.98E-10
	Euclidean Distance	0.27960842	0.050150481	-0.222560406	-0.006897533
	Onset_to_1st_CT	1	0.104529129	-0.79597176	-0.099499111
	Onset_To_Arrival_1st	0.494565217	0.100905272	-0.393659946	7.24E-10
75	DIDI Time (Door-In-Door-In)	0.260902831	0.143075746	0	-0.117827085
	Driving Distance	0.3925	0.02	0	-0.3725
	Euclidean Distance	0.408119521	0.010493314	0	-0.397626207
	Onset_to_1st_CT	0.070930233	0.038953488	0	-0.031976745
	Onset_To_Arrival_1st	0.000905797	0.000905797	0	0
76	DIDI Time (Door-In-Door-In)	0.433817904	0.26013772	0	-0.173680184
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.146511628	0.1	0	-0.046511628
	Onset_To_Arrival_1st	0.184782609	0.139492754	0	-0.045289855
77	DIDI Time (Door-In-Door-In)	0.09716909	0.09716909	0	1.85E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.115697674	0.070925793	0	-0.044771881
	Onset_To_Arrival_1st	0.147644928	0.063654717	0	-0.083990211
78	DIDI Time (Door-In-Door-In)	0.55317521	0.143075746	0	-0.410099464
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.409302326	0.038953488	0	-0.370348838
	Onset_To_Arrival_1st	0.529891304	0.000905797	0	-0.528985507

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

79	DIDI Time (Door-In-Door-In)	0.488905891	0.153641233	-0.27523998	-0.060024678
	Driving Distance	1	0.437028712	-0.56297129	2.25E-09
	Euclidean Distance	1	0.409865437	-0.56297129	-0.027163273
	Onset_to_1st_CT	0.05755814	0.02515456	-0.03240358	0
	Onset_To_Arrival_1st	0.029891304	0.013063358	-0.016827946	0
80	DIDI Time (Door-In-Door-In)	0.166794185	0.166794185	0	0
	Driving Distance	0.755	0.755	0	0
	Euclidean Distance	0.70925843	0.70925843	0	0
	Onset_to_1st_CT	0.015697674	0.015697674	0	0
	Onset_To_Arrival_1st	0.015398551	0.015398551	0	0
81	DIDI Time (Door-In-Door-In)	0.181331293	0.10475803	-0.076573262	-1.19E-09
	Driving Distance	0.3925	0.22118186	-0.16574638	-0.00557176
	Euclidean Distance	0.408119521	0.235777269	-0.17234225	-2.22E-09
	Onset_to_1st_CT	0.087209302	0.050382228	-0.036827073	-8.91E-10
	Onset_To_Arrival_1st	0.120471014	0.069598059	-0.050872954	-1.22E-09
82	DIDI Time (Door-In-Door-In)	0.295332823	0.120485015	-0.146720012	-0.028127797
	Driving Distance	0.755	0.34992854	-0.375080587	-0.029990872
	Euclidean Distance	0.70925843	0.356902048	-0.352356382	-2.00E-10
	Onset_to_1st_CT	0.065116279	0.032766806	-0.032349473	-3.68E-10
	Onset_To_Arrival_1st	0.095108696	0.047859126	-0.04724957	-2.16E-10
83	DIDI Time (Door-In-Door-In)	0.450650344	0.450650344	0	0
	Driving Distance	0.755	0.755	0	0
	Euclidean Distance	0.70925843	0.70925843	0	0
	Onset_to_1st_CT	0.031976744	0.031976744	0	0
	Onset_To_Arrival_1st	0.000905797	0.000905797	0	0
84	DIDI Time (Door-In-Door-In)	0.112471308	0.112471308	0	0
	Driving Distance	0.2625	0.2625	0	0
	Euclidean Distance	0.27960842	0.27960842	0	0
	Onset_to_1st_CT	0.023255814	0.023255814	0	0
	Onset_To_Arrival_1st	0.057971014	0.057971014	0	0
85	DIDI Time (Door-In-Door-In)	0.598316756	0.143075746	0	-0.45524101
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.093604651	0.038953488	0	-0.054651163
	Onset_To_Arrival_1st	0.095108696	0.000905797	0	-0.094202899
86	DIDI Time (Door-In-Door-In)	0.039020658	0.039020658	0	0
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.131976744	0.131976744	0	0
	Onset_To_Arrival_1st	0.150362319	0.150362319	0	0

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

87	DIDI Time (Door-In-Door-In)	0.373374139	0.311400153	0	-0.061973986
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.154651163	0.116860465	0	-0.037790698
	Onset_To_Arrival_1st	0.051630435	0.038949275	0	-0.01268116
88	DIDI Time (Door-In-Door-In)	0.197398623	0.084581146	-0.112817476	-1.11E-09
	Driving Distance	0.5425	0.186082313	-0.310050191	-0.046367495
	Euclidean Distance	0.533943311	0.194803662	-0.305159863	-0.033979786
	Onset_to_1st_CT	0.120930233	0.051816054	-0.069114179	-5.27E-10
	Onset_To_Arrival_1st	0.180253623	0.077234875	-0.103018747	-8.29E-10
89	DIDI Time (Door-In-Door-In)	0.234889059	0.145935913	-0.088953147	3.94E-10
	Driving Distance	1	0.487569757	-0.37870281	-0.133727433
	Euclidean Distance	1	0.466422097	-0.37870281	-0.154875093
	Onset_to_1st_CT	0.022674419	0.014087553	-0.008586866	0
	Onset_To_Arrival_1st	0.031702899	0.019696922	-0.012005977	1.01E-10
90	DIDI Time (Door-In-Door-In)	0.068859985	0.068859985	0	1.50E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.425	0.095708042	0	-0.329291958
	Onset_To_Arrival_1st	0.56884058	0.09828187	0	-0.47055871
91	DIDI Time (Door-In-Door-In)	0.331293037	0.143075746	0	-0.188217291
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.340697674	0.038953488	0	-0.301744186
	Onset_To_Arrival_1st	0.369565217	0.000905797	0	-0.36865942
92	DIDI Time (Door-In-Door-In)	0.280030604	0.100218783	-0.17981182	-5.70E-10
	Driving Distance	0.8975	0.272256696	-0.576298114	-0.048945191
	Euclidean Distance	0.800531064	0.286498146	-0.514032916	-1.69E-09
	Onset_to_1st_CT	0.088953488	0.031835129	-0.057118359	-1.49E-10
	Onset_To_Arrival_1st	0.120471014	0.043114782	-0.077356232	-1.94E-10
93	DIDI Time (Door-In-Door-In)	0.218056618	0.113721626	-0.104334991	-1.61E-10
	Driving Distance	0.3925	0.20469793	-0.187802069	-4.50E-10
	Euclidean Distance	0.408119521	0.21207711	-0.195275645	-0.000766766
	Onset_to_1st_CT	0.050581395	0.026379381	-0.024202014	0
	Onset_To_Arrival_1st	0.054347826	0.028343663	-0.026004164	0

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

94	**DIDI Time (Door-In-Door-In)**	**0.123182862**	**0.084980777**	**-0.038202084**	**-8.07E-10**
	Driving Distance	**0.2625**	**0.18109219**	**-0.08140781**	**-5.00E-10**
	Euclidean Distance	**0.27960842**	**0.189265857**	**-0.086713558**	**-0.003629004**
	Onset_to_1st_CT	**0.08255814**	**0.056954797**	**-0.025603342**	**-4.68E-10**
	Onset_To_Arrival_1st	**0.120471014**	**0.069219808**	**-0.037361072**	**-0.013890134**
95	**DIDI Time (Door-In-Door-In)**	**0.188982402**	**0.143075746**	**0**	**-0.045906656**
	Driving Distance	**0.02**	**0.02**	**0**	**0**
	Euclidean Distance	**0.010493314**	**0.010493314**	**0**	**0**
	Onset_to_1st_CT	**0.398255814**	**0.038953488**	**0**	**-0.359302326**
	Onset_To_Arrival_1st	**0.596014493**	**0.000905797**	**0**	**-0.595108696**
96	**DIDI Time (Door-In-Door-In)**	**0.100994644**	**0.082818812**	**-0.018175831**	**-2.73E-10**
	Driving Distance	**0.23175**	**0.190042353**	**-0.041707647**	**-3.38E-10**
	Euclidean Distance	**0.260733252**	**0.199198328**	**-0.046923712**	**-0.014611212**
	Onset_to_1st_CT	**0.070348837**	**0.057688278**	**-0.012660558**	**-1.28E-10**
	Onset_To_Arrival_1st	**0.092391304**	**0.075763801**	**-0.016627503**	**-2.11E-10**
97	**DIDI Time (Door-In-Door-In)**	**0.128538638**	**0.090935893**	**-0.037602746**	**8.53E-10**
	Driving Distance	**0.3925**	**0.251959087**	**-0.114822111**	**-0.025718802**
	Euclidean Distance	**0.408119521**	**0.268895239**	**-0.119391452**	**-0.01983283**
	Onset_to_1st_CT	**0.064534884**	**0.045655823**	**-0.018879061**	**3.98E-10**
	Onset_To_Arrival_1st	**0.081521739**	**0.057673337**	**-0.023848403**	**5.05E-10**
98	**DIDI Time (Door-In-Door-In)**	**0.183626626**	**0.087247465**	**-0.09637916**	**-1.09E-09**
	Driving Distance	**0.5425**	**0.246664751**	**-0.284739176**	**-0.011096073**
	Euclidean Distance	**0.533943311**	**0.253695237**	**-0.28024807**	**-3.06E-09**
	Onset_to_1st_CT	**0.098837209**	**0.046961033**	**-0.051876176**	**-1.99E-10**
	Onset_To_Arrival_1st	**0.128623188**	**0.061113399**	**-0.067509789**	**-4.08E-10**
99	**DIDI Time (Door-In-Door-In)**	**0.12165264**	**0.105619803**	**-0.016032837**	**4.70E-10**
	Driving Distance	**0.2625**	**0.227904618**	**-0.034595384**	**2.11E-09**
	Euclidean Distance	**0.27960842**	**0.24121609**	**-0.036850136**	**-0.001542194**
	Onset_to_1st_CT	**0.025581395**	**0.022209974**	**-0.003371422**	**1.93E-10**
	Onset_To_Arrival_1st	**0.050724638**	**0.04403954**	**-0.006685098**	**4.64E-10**
100	**DIDI Time (Door-In-Door-In)**	**0.166794185**	**0.042031878**	**-0.124762307**	**1.62E-10**
	Driving Distance	**0.23175**	**0.043554746**	**-0.173349357**	**-0.014845897**
	Euclidean Distance	**0.260733252**	**0.036633265**	**-0.195028874**	**-0.029071113**
	Onset_to_1st_CT	**0.473255814**	**0.119259737**	**-0.353996078**	**2.81E-10**
	Onset_To_Arrival_1st	**0.725543478**	**0.14150679**	**-0.542707639**	**-0.041329049**

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

101	**DIDI Time (Door-In-Door-In)**	**0.122417751**	**0.107702054**	**-0.014715697**	**2.61E-10**
	Driving Distance	**0.2625**	**0.230945177**	**-0.031554823**	**5.55E-10**
	Euclidean Distance	**0.27960842**	**0.24459036**	**-0.033611407**	**-0.001406653**
	Onset_to_1st_CT	**0.015697674**	**0.013810675**	**-0.001886999**	**0**
	Onset_To_Arrival_1st	**0.050724638**	**0.043494817**	**-0.00609755**	**-0.001132271**
102	**DIDI Time (Door-In-Door-In)**	**0.117827085**	**0.08026098**	**-0.037566105**	**-2.51E-10**
	Driving Distance	**0.2625**	**0.157589652**	**-0.083691305**	**-0.021219042**
	Euclidean Distance	**0.27960842**	**0.163183846**	**-0.08914588**	**-0.027278694**
	Onset_to_1st_CT	**0.087209302**	**0.059404882**	**-0.02780442**	**3.56E-10**
	Onset_To_Arrival_1st	**0.132246377**	**0.086634854**	**-0.042163322**	**-0.003448202**
103	**DIDI Time (Door-In-Door-In)**	**0.218821729**	**0.103809435**	**-0.115012294**	**0**
	Driving Distance	**0.2625**	**0.124530488**	**-0.137969512**	**-2.90E-10**
	Euclidean Distance	**0.27960842**	**0.129560159**	**-0.146961665**	**-0.003086596**
	Onset_to_1st_CT	**0.140116279**	**0.066471423**	**-0.073644856**	**-1.16E-10**
	Onset_To_Arrival_1st	**0.09692029**	**0.045979166**	**-0.050941124**	**0**
104	**DIDI Time (Door-In-Door-In)**	**0.111706197**	**0.111706197**	**0**	**0**
	Driving Distance	**0.2625**	**0.2625**	**0**	**0**
	Euclidean Distance	**0.27960842**	**0.27960842**	**0**	**0**
	Onset_to_1st_CT	**0.004069767**	**0.004069767**	**0**	**0**
	Onset_To_Arrival_1st	**0.038043478**	**0.038043478**	**0**	**0**
105	**DIDI Time (Door-In-Door-In)**	**0.140780413**	**0.079711343**	**-0.061069071**	**6.63E-10**
	Driving Distance	**0.2625**	**0.148630247**	**-0.113869754**	**1.68E-09**
	Euclidean Distance	**0.27960842**	**0.153241119**	**-0.121291208**	**-0.005076093**
	Onset_to_1st_CT	**0.109302326**	**0.06188812**	**-0.047414206**	**-2.07E-10**
	Onset_To_Arrival_1st	**0.163949275**	**0.087599799**	**-0.071119481**	**-0.005229996**
106	**DIDI Time (Door-In-Door-In)**	**0.149961744**	**0.11215243**	**-0.037809312**	**-1.98E-09**
	Driving Distance	**0.23175**	**0.17331971**	**-0.058430289**	**-1.03E-09**
	Euclidean Distance	**0.260733252**	**0.181627444**	**-0.065737731**	**-0.013368077**
	Onset_to_1st_CT	**0.085465116**	**0.063917104**	**-0.02154801**	**-1.50E-09**
	Onset_To_Arrival_1st	**0.11865942**	**0.088742248**	**-0.02991717**	**-1.84E-09**
107	**DIDI Time (Door-In-Door-In)**	**0.127008416**	**0.074743689**	**-0.052264727**	**-7.07E-10**
	Driving Distance	**0.2625**	**0.139182372**	**-0.108020328**	**-0.0152973**
	Euclidean Distance	**0.27960842**	**0.142756311**	**-0.115060545**	**-0.021791564**
	Onset_to_1st_CT	**0.11744186**	**0.069113829**	**-0.048328031**	**0**
	Onset_To_Arrival_1st	**0.178442029**	**0.095160563**	**-0.073429967**	**-0.009851499**

Table 29: Original Values, Target Values, Radial, and Non-radial for All 115 DMUs in the First Scenario.

108	DIDI Time (Door-In-Door-In)	0.140015302	0.114429038	-0.025586265	2.76E-10
	Driving Distance	0.2625	0.214530998	-0.047969003	1.63E-09
	Euclidean Distance	0.27960842	0.222423414	-0.05109538	-0.006089626
	Onset_to_1st_CT	0.023837209	0.01948122	-0.004355989	0
	Onset_To_Arrival_1st	0.036231884	0.029610904	-0.00662098	2.08E-10
109	DIDI Time (Door-In-Door-In)	0.10558531	0.10558531	0	0
	Driving Distance	0.3925	0.3925	0	0
	Euclidean Distance	0.408119521	0.408119521	0	0
	Onset_to_1st_CT	0.018023256	0.018023256	0	0
	Onset_To_Arrival_1st	0.027173913	0.027173913	0	0
110	DIDI Time (Door-In-Door-In)	0.168324407	0.09974092	-0.068583487	-1.94E-10
	Driving Distance	0.5425	0.300968695	-0.221040681	-0.020490624
	Euclidean Distance	0.533943311	0.316389038	-0.217554273	-4.23E-10
	Onset_to_1st_CT	0.051162791	0.030316601	-0.02084619	-1.48E-10
	Onset_To_Arrival_1st	0.070652174	0.041865068	-0.028787105	-2.23E-10
111	DIDI Time (Door-In-Door-In)	0.135424637	0.109886872	-0.025537766	5.56E-10
	Driving Distance	0.2625	0.212998938	-0.049501064	1.72E-09
	Euclidean Distance	0.27960842	0.224674467	-0.052727292	-0.002206661
	Onset_to_1st_CT	0.020348837	0.016511545	-0.003837292	0
	Onset_To_Arrival_1st	0.054347826	0.041559461	-0.010248667	-0.002539697
112	DIDI Time (Door-In-Door-In)	0.342769702	0.123750571	-0.219019131	0
	Driving Distance	0.4875	0.153130771	-0.311497271	-0.022871959
	Euclidean Distance	0.438287798	0.158235588	-0.280052211	1.19E-09
	Onset_to_1st_CT	0.040697674	0.014693132	-0.026004542	0
	Onset_To_Arrival_1st	0.060688406	0.021858015	-0.038777996	-5.24E-05
113	DIDI Time (Door-In-Door-In)	0.7482785	0.131793193	-0.616485308	4.37E-10
	Driving Distance	0.3925	0.069130448	-0.323369552	-2.30E-10
	Euclidean Distance	0.408119521	0.063858024	-0.33623803	-0.008023468
	Onset_to_1st_CT	0.149418605	0.026316879	-0.123101726	0
	Onset_To_Arrival_1st	0.054347826	0.009572203	-0.044775623	0
114	DIDI Time (Door-In-Door-In)	0.167559296	0.105766301	-0.061792995	1.26E-10
	Driving Distance	0.3925	0.24527341	-0.144747269	-0.002479321
	Euclidean Distance	0.408119521	0.257612042	-0.15050748	6.12E-10
	Onset_to_1st_CT	0.043023256	0.027157017	-0.015866239	0
	Onset_To_Arrival_1st	0.060688406	0.038307563	-0.022380843	0

Table 29: Original Values, Target Values, Radial, and Non-radial for Efficient DMUs in the First Scenario.

115	DIDI Time (Door-In-Door-In)	0.357306809	0.114901669	-0.223619037	-0.018786102
	Driving Distance	0.755	0.246872926	-0.47251373	-0.035613344
	Euclidean Distance	0.70925843	0.265371877	-0.443886551	-2.10E-09
	Onset_to_1st_CT	0.11627907	0.043506279	-0.072772791	-5.40E-10
	Onset_To_Arrival_1st	0.153985507	0.057614293	-0.096371214	-4.32E-10

Table 30: Original Values, Target Values, Radial, and Non-radial for Efficient DMUs After Applying Super-efficiency in the First Scenario.

DMUs	Category	Original	Target	Radial	Non-radial
8	DIDI Time (Door-In-Door-In)	1	0.143075746	0	-0.856924254
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.04244186	0.038953488	0	-0.003488372
	Onset_To_Arrival_1st	0.048007246	0.000905797	0	-0.047101449
11	DIDI Time (Door-In-Door-In)	0.321346595	0.143075746	0	-0.178270849
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.362209302	0.038953488	0	-0.323255814
	Onset_To_Arrival_1st	0.428442029	0.000905797	0	-0.427536232
14	DIDI Time (Door-In-Door-In)	0.116296863	0.116296863	0	-1.01266E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.097093023	0.047284271	0	-0.049808752
	Onset_To_Arrival_1st	0.125	0.032012776	0	-0.092987224
16	DIDI Time (Door-In-Door-In)	0.140015302	0.140015302	0	-1.53256E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.103488372	0.041293882	0	-0.06219449
	Onset_To_Arrival_1st	0.124094203	0.004921305	0	-0.119172898
17	DIDI Time (Door-In-Door-In)	0.207345065	0.139250191	0	-0.068094874
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.587790698	0.026744186	0	-0.561046512
	Onset_To_Arrival_1st	0.808876812	0.000905797	0	-0.807971015

Table 30: Original Values, Target Values, Radial, and Non-radial for Efficient DMUs After Applying Super-efficiency in the First Scenario.

18	DIDI Time (Door-In-Door-In)	0.143075746	0.284853648	2.850147552	-2.70836965
	Driving Distance	0.02	0.215823712	0.398411	-0.202587288
	Euclidean Distance	0.010493314	0.219525904	0.209032586	3.8737E-09
	Onset_to_1st_CT	0.038953488	0.092714885	0.775974905	-0.722213508
	Onset_To_Arrival_1st	0.000905797	0.018949771	0.018043974	0
19	DIDI Time (Door-In-Door-In)	0.10558531	0.10558531	0	0
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.233139535	0.067623315	0	-0.16551622
	Onset_To_Arrival_1st	0.22192029	0.050095772	0	-0.171824518
20	DIDI Time (Door-In-Door-In)	0.022953328	0.039020658	0.01606733	4E-10
	Driving Distance	0.02	0.02	0.014	-0.014
	Euclidean Distance	0.010493314	0.010493314	0.00734532	-0.00734532
	Onset_to_1st_CT	0.130813953	0.131976744	0.091569767	-0.090406976
	Onset_To_Arrival_1st	0.158514493	0.150362319	0.110960145	-0.119112319
21	DIDI Time (Door-In-Door-In)	0.301453711	0.143075746	0	-0.158377965
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.294186047	0.038953488	0	-0.255232559
	Onset_To_Arrival_1st	0.237318841	0.000905797	0	-0.236413044
22	DIDI Time (Door-In-Door-In)	0.139250191	0.108338009	4.594913051	-4.625825233
	Driving Distance	0.02	0.340532096	0.6599507	-0.339418604
	Euclidean Distance	0.010493314	0.356746809	0.346253496	-1.27526E-09
	Onset_to_1st_CT	0.026744186	0.013839793	0.882492214	-0.895396606
	Onset_To_Arrival_1st	0.000905797	0.030794865	0.029889068	-1.32855E-10
23	DIDI Time (Door-In-Door-In)	0.434583015	0.143075746	0	-0.291507269
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.263372093	0.038953488	0	-0.224418605
	Onset_To_Arrival_1st	0.000905797	0.000905797	0	0
24	DIDI Time (Door-In-Door-In)	0.311400153	0.143075746	0	-0.168324407
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.116860465	0.038953488	0	-0.077906977
	Onset_To_Arrival_1st	0.038949275	0.000905797	0	-0.038043478
25	DIDI Time (Door-In-Door-In)	0.413925019	0.143075746	0	-0.270849273
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.30872093	0.038953488	0	-0.269767442
	Onset_To_Arrival_1st	0.382246377	0.000905797	0	-0.38134058

Table 30: Original Values, Target Values, Radial, and Non-radial for Efficient DMUs After Applying Super-efficiency in the First Scenario.

26	DIDI Time (Door-In-Door-In)	0.092578424	0.104823181	0.012244756	1.6652E-09
	Driving Distance	0.2625	0.240246334	0.034719195	-0.056972861
	Euclidean Distance	0.27960842	0.256962051	0.036982016	-0.059628385
	Onset_to_1st_CT	0.037790698	0.042789032	0.004998334	7.1696E-10
	Onset_To_Arrival_1st	0.055253623	0.062561667	0.007308043	9.51945E-10
29	DIDI Time (Door-In-Door-In)	0.167559296	0.167559295	0	-8.09042E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.087790698	0.050285412	0	-0.037505286
	Onset_To_Arrival_1st	0.059782609	0.006439394	0	-0.053343215
30	DIDI Time (Door-In-Door-In)	0.302983933	0.143075746	0	-0.159908187
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.145930233	0.038953488	0	-0.106976745
	Onset_To_Arrival_1st	0.072463768	0.000905797	0	-0.071557971
34	DIDI Time (Door-In-Door-In)	0.547819434	0.143075746	0	-0.404743688
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.159883721	0.038953488	0	-0.120930233
	Onset_To_Arrival_1st	0.136775362	0.000905797	0	-0.135869565
35	DIDI Time (Door-In-Door-In)	0.101759755	0.101759754	0	-7.56965E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.549418605	0.122903758	0	-0.426514847
	Onset_To_Arrival_1st	0.843297101	0.147278221	0	-0.69601888
37	DIDI Time (Door-In-Door-In)	0.141545524	0.141545525	0	6.27274E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.288953488	0.040123685	0	-0.248829803
	Onset_To_Arrival_1st	0.401268116	0.002913551	0	-0.398354565
41	DIDI Time (Door-In-Door-In)	0.26013772	0.040063952	0.079800627	-0.299874395
	Driving Distance	0.02	0.02290061	0.00613526	-0.00323465
	Euclidean Distance	0.010493314	0.013712275	0.00321896	3.72905E-10
	Onset_to_1st_CT	0.1	0.130676302	0.0306763	2.49115E-09
	Onset_To_Arrival_1st	0.139492754	0.149311373	0.042791216	-0.032972597
42	DIDI Time (Door-In-Door-In)	0.126243305	0.112471308	0	-0.013771997
	Driving Distance	0.2625	0.2625	0	0
	Euclidean Distance	0.27960842	0.27960842	0	0
	Onset_to_1st_CT	0.023255814	0.023255814	0	0
	Onset_To_Arrival_1st	0.0625	0.057971014	0	-0.004528986

Table 30: Original Values, Target Values, Radial, and Non-radial for Efficient DMUs After Applying Super-efficiency in the First Scenario.

45	DIDI Time (Door-In-Door-In)	0.096403979	0.097909037	0.027506542	-0.026001485
	Driving Distance	0.23175	0.297874249	0.066124254	-4.835E-09
	Euclidean Distance	0.260733252	0.310468413	0.074393924	-0.024658763
	Onset_to_1st_CT	0.108139535	0.036203847	0.030854999	-0.102790687
	Onset_To_Arrival_1st	0.04076087	0.052390997	0.011630128	-8.89657E-10
51	DIDI Time (Door-In-Door-In)	0.185156848	0.066835863	-0.118320986	1.15462E-09
	Driving Distance	0.3925	0.132149409	-0.250819711	-0.00953088
	Euclidean Distance	0.408119521	0.134951459	-0.260801071	-0.012366992
	Onset_to_1st_CT	0.200581395	0.072403644	-0.128177751	5.08948E-10
	Onset_To_Arrival_1st	0.307065217	0.101360705	-0.196224226	-0.009480286
52	DIDI Time (Door-In-Door-In)	0.589135425	0.143075746	0	-0.446059679
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.079069767	0.038953488	0	-0.040116279
	Onset_To_Arrival_1st	0.042572464	0.000905797	0	-0.041666667
64	DIDI Time (Door-In-Door-In)	0.122417751	0.122417751	0	-2.28138E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.331395349	0.05742134	0	-0.273974009
	Onset_To_Arrival_1st	0.490942029	0.030577312	0	-0.460364717
66	DIDI Time (Door-In-Door-In)	0.612853864	0.139250191	0	-0.473603673
	Driving Distance	0.3925	0.02	0	-0.3725
	Euclidean Distance	0.408119521	0.010493314	0	-0.397626207
	Onset_to_1st_CT	0.058139535	0.026744186	0	-0.031395349
	Onset_To_Arrival_1st	0.000905797	0.000905797	0	0
71	DIDI Time (Door-In-Door-In)	0.351185922	0.143075746	0	-0.208110176
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.623255814	0.038953488	0	-0.584302326
	Onset_To_Arrival_1st	0.72192029	0.000905797	0	-0.721014493
72	DIDI Time (Door-In-Door-In)	0.214996174	0.143075746	0	-0.071920428
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.109883721	0.038953488	0	-0.070930233
	Onset_To_Arrival_1st	0.075181159	0.000905797	0	-0.074275362
73	DIDI Time (Door-In-Door-In)	0.042081102	0.042081102	0	-2.8775E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.413372093	0.11618649	0	-0.297185603
	Onset_To_Arrival_1st	0.786231884	0.133417567	0	-0.652814317

Table 30: Original Values, Target Values, Radial, and Non-radial for Efficient DMUs After Applying Super-efficiency in the First Scenario.

75	DIDI Time (Door-In-Door-In)	0.260902831	0.143075746	0	-0.117827085
	Driving Distance	0.3925	0.02	0	-0.3725
	Euclidean Distance	0.408119521	0.010493314	0	-0.397626207
	Onset_to_1st_CT	0.070930233	0.038953488	0	-0.031976745
	Onset_To_Arrival_1st	0.000905797	0.000905797	0	0
76	DIDI Time (Door-In-Door-In)	0.433817904	0.039020658	0	-0.394797246
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.146511628	0.131976744	0	-0.014534884
	Onset_To_Arrival_1st	0.184782609	0.150362319	0	-0.03442029
77	DIDI Time (Door-In-Door-In)	0.09716909	0.09716909	0	1.85098E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.115697674	0.070925793	0	-0.044771881
	Onset_To_Arrival_1st	0.147644928	0.063654717	0	-0.083990211
78	DIDI Time (Door-In-Door-In)	0.55317521	0.143075746	0	-0.410099464
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.409302326	0.038953488	0	-0.370348838
	Onset_To_Arrival_1st	0.529891304	0.000905797	0	-0.528985507
80	DIDI Time (Door-In-Door-In)	0.166794185	0.198163734	0.08830281	-0.056933261
	Driving Distance	0.755	1	0.399705909	-0.154705909
	Euclidean Distance	0.70925843	1	0.375489782	-0.084748212
	Onset_to_1st_CT	0.015697674	0.023837209	0.008310534	-0.000170999
	Onset_To_Arrival_1st	0.015398551	0.023550725	0.008152175	-6.02302E-10
83	DIDI Time (Door-In-Door-In)	0.450650344	0.143385116	0.094048744	-0.401313972
	Driving Distance	0.755	0.029586955	0.157565178	-0.882978223
	Euclidean Distance	0.70925843	0.01960764	0.148019114	-0.837669904
	Onset_to_1st_CT	0.031976744	0.038650151	0.006673406	1.41729E-09
	Onset_To_Arrival_1st	0.000905797	0.001094833	0.000189036	0
84	DIDI Time (Door-In-Door-In)	0.112471308	0.12178356	0.009312253	-1.15809E-09
	Driving Distance	0.2625	0.2625	0.021734134	-0.021734134
	Euclidean Distance	0.27960842	0.27960842	0.023150654	-0.023150654
	Onset_to_1st_CT	0.023255814	0.025181318	0.001925505	-2.57579E-10
	Onset_To_Arrival_1st	0.057971014	0.061540038	0.004799809	-0.001230784
85	DIDI Time (Door-In-Door-In)	0.598316756	0.143075746	0	-0.45524101
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.093604651	0.038953488	0	-0.054651163
	Onset_To_Arrival_1st	0.095108696	0.000905797	0	-0.094202899

Table 30: Original Values, Target Values, Radial, and Non-radial for Efficient DMUs After Applying Super-efficiency in the First Scenario.

86	DIDI Time (Door-In-Door-In)	0.039020658	0.144813905	0.105793245	1.62995E-09
	Driving Distance	0.02	0.044073699	0.054224224	-0.030150525
	Euclidean Distance	0.010493314	0.038942905	0.02844959	4.2935E-10
	Onset_to_1st_CT	0.131976744	0.375350207	0.357816826	-0.114443364
	Onset_To_Arrival_1st	0.150362319	0.558026327	0.407664003	4.30545E-09
87	DIDI Time (Door-In-Door-In)	0.373374139	0.143075746	0	-0.230298393
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.154651163	0.038953488	0	-0.115697675
	Onset_To_Arrival_1st	0.051630435	0.000905797	0	-0.050724638
90	DIDI Time (Door-In-Door-In)	0.068859985	0.068859985	0	1.49645E-10
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.425	0.095708042	0	-0.329291958
	Onset_To_Arrival_1st	0.56884058	0.09828187	0	-0.47055871
91	DIDI Time (Door-In-Door-In)	0.331293037	0.143075746	0	-0.188217291
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.340697674	0.038953488	0	-0.301744186
	Onset_To_Arrival_1st	0.369565217	0.000905797	0	-0.36865942
95	DIDI Time (Door-In-Door-In)	0.188982402	0.143075746	0	-0.045906656
	Driving Distance	0.02	0.02	0	0
	Euclidean Distance	0.010493314	0.010493314	0	0
	Onset_to_1st_CT	0.398255814	0.038953488	0	-0.359302326
	Onset_To_Arrival_1st	0.596014493	0.000905797	0	-0.595108696
104	DIDI Time (Door-In-Door-In)	0.111706197	0.112471308	0.095748207	-0.094983096
	Driving Distance	0.2625	0.2625	0.22500009	-0.22500009
	Euclidean Distance	0.27960842	0.27960842	0.239664456	-0.239664456
	Onset_to_1st_CT	0.004069767	0.00755814	0.003488373	-1.09634E-10
	Onset_To_Arrival_1st	0.038043478	0.036231884	0.032608708	-0.034420302
109	DIDI Time (Door-In-Door-In)	0.10558531	0.11570648	0.010121165	5.05279E-09
	Driving Distance	0.3925	0.225054308	0.037624147	-0.205069839
	Euclidean Distance	0.408119521	0.234514254	0.039121399	-0.212726666
	Onset_to_1st_CT	0.018023256	0.019750925	0.001727668	8.01653E-10
	Onset_To_Arrival_1st	0.027173913	0.029778743	0.002604829	1.07684E-09

Table 31: Original Values, Target Values, Radial, and Non-radial of All 115 DMUs.

DMUs	PSCs	Efficiency	Reference Set (Efficient DMUs number)	Peer Weight (Lambdas)	Peer Count	Classification
1	2	0.37047866	42,41,18	0.51716649,0.11235486,0.37047866	-	IRS
2	6	0.53481983	26,104,109,22	0.25333833,0.13750643,0.42725536,0.18189988	-	IRS
3	7	0.56055283	20,109,104	0.089943553,0.7598555,0.15020095	-	IRS
4	2	0.99369193	86,26,109	0.13781283,0.22271624,0.63947093	-	IRS
5	5	0.44884999	22,109,104	0.25824888,0.56042054,0.18133058	-	IRS
6	7	0.49159373	86,26	0.07822104,0.92177896	-	IRS
7	2	0.73559787	45,26,86	0.014176412,0.94811468,0.037708913	-	IRS
8	8	1	18	1	-	CRS
9	3	0.70605276	86,26,22,104	0.17991818,0.005377071,0.22780253,0.58690222	-	IRS
10	10	0.20650682	20,26,86,104	0.20650682,0.002264888,0.27546761,0.51576069	-	IRS
11	8	1	18	1	-	CRS
12	9	0.87392301	84,26,45,86	0.13965811,0.70624827,0.020177068,0.13391655	-	IRS
13	2	0.52225037	45,26,18	0.007132385,0.50035329,0.49251433	-	IRS
14	8	1	20,18	0.22292994,0.77707006	-	CRS
15	2	0.27492907	45,18,41	0.40645232,0.27492907,0.31861861	-	IRS
16	8	1	20,18	0.025477709,0.97452229	-	CRS
17	8	1	18	1	-	CRS
18	8	1	18	1	40	CRS
19	8	1	20,18	0.31210191,0.68789809	-	CRS
20	8	1	20	1	27	CRS
21	8	1	18	1	-	CRS
22	8	1	22	1	29	CRS
23	8	1	18	1	-	CRS
24	8	1	24	1	3	CRS
25	8	1	18	1	-	CRS
26	9	1	26	1	35	CRS
27	6	0.3276777	20,26,18,86	0.063022726,0.6111437,0.26465497,0.0611786	-	IRS
28	10	0.66201662	84,80,18	0.57079399,0.21393703,0.21526898	-	IRS
29	8	1	24,18	0.14545454,0.85454546	-	CRS
30	8	1	18	1	-	CRS
31	7	0.84328033	84,45,80	0.2345336,0.023158974,0.74230742	-	IRS
32	3	0.41663489	20,86,104	0.41663489,0.28255179,0.30081332	-	IRS
33	10	0.20650682	20,26,86,104	0.20650682,0.002264888,0.27546761,0.51576069	-	IRS
34	8	1	18	1	-	CRS
35	8	1	86,41	0.71626298,0.28373702	-	CRS
36	5	0.40122734	86,26,104	0.33716843,0.1292101,0.53362145	-	IRS
37	8	1	20,18	0.012738854,0.98726115	-	CRS
38	2	0.59335672	45,26,22,86	0.015443781,0.84648721,0.13241236,0.005656642	-	IRS
39	7	0.39803553	86,26	0.085253302,0.9147467	-	IRS
40	2	0.87347816	26,109,104	0.28041201,0.45007301,0.26951498	-	IRS
41	8	1	41	1	11	CRS
42	9	1	84	1	2	CRS
43	10	0.40999737	80,22,104	0.42891541,0.26285966,0.30822493	-	IRS
44	6	0.59054233	86,26	0.21847034,0.78152966	-	IRS
45	3	1	45	1	22	CRS
46	2	0.61392984	86,26	0.19374682,0.80625318	-	IRS
47	10	0.80579527	45,26,80	0.019475547,0.077394584,0.90312987	-	IRS
48	9	0.74147996	20,22,104	0.11946719,,0.16037409,0.72015872	-	IRS
49	10	0.14632709	45,20,86	0.51207802,0.14632709,0.34159489	-	IRS
50	7	0.5620658	84,80,18	0.46881456,0.37493502,0.15625042	-	IRS
51	1	0.36096889	20,86,104	0.36096889,0.17655932,0.46247179	-	IRS
52	8	1	18	1	-	CRS
53	3	0.80681012	84,42,18	0.044193713,0.64437637,0.31142991	-	IRS

Table 31: Original Values, Target Values, Radial, and Non-radial of All 115 DMUs.

54	7	0.17512331	84,86,18,41	0.42254918,0.38951658,0.17512331,0.012810927	-	IRS
55	4	0.84850463	45,26,109,22	0.022023331,0.65823983,0.033166035,0.2865708	-	IRS
56	3	0.62796032	86,22,104	0.13494544,0.34740588,0.51764868	-	IRS
57	9	0.99443054	26,104,109,22	0.037077433,0.83573775,0.078873382,0.048311438	-	IRS
58	9	0.57679494	86,22,104	0.26732997,0.1907786,0.54189143	-	IRS
59	1	0.71707895	20,104	0.15209368,0.84790632	-	IRS
60	5	0.45543838	84,26,45,80	0.60782398,0.066288128,0.12269898,0.20318891	-	IRS
61	10	0.20353869	20,26,18,86	0.082022798,0.71733384,0.12151589,0.079127478	-	IRS
62	9	0.50110212	22,104	0.54004409,0.45995591	-	IRS
63	3	0.63495079	86,22,104	0.18858683,0.28708391,0.52432926	-	IRS
64	8	1	20,18	0.17197452,0.82802548	-	CRS
65	9	0.90015285	84,45,41	0.81453954,0.087884085,0.097576372	-	IRS
66	2	1	18	1	-	CRS
67	7	0.38917901	84,26,45,86	0.35169438,0.52595904,0.117269,0.005077586	-	IRS
68	9	0.1770921	20,26,18,86	0.16599167,0.10922341,0.011100429,0.71368449	-	IRS
69	3	0.23178621	20,86,104	0.23178621,0.64141539,0.1267984	-	IRS
70	1	0.43720876	86,26,22,104	0.011446232,0.480287,0.36450811,0.14375866	-	IRS
71	8	1	18	1	-	CRS
72	8	1	18	1	-	CRS
73	8	1	20,18	0.84076433,0.15923567	-	CRS
74	9	0.20402824	45,86,18,41	0.15847657,0.4908072,0.20402824,0.14668799	-	IRS
75	1	1	18	1	-	CRS
76	8	1	41	1	-	CRS
77	8	1	86,22	0.41984732,0.5815268	-	CRS
78	8	1	18	1	-	CRS
79	10	0.43702871	84,80,18	0.075254492,0.54255714,0.38218837	-	IRS
80	7	1	80	1	10	CRS
81	1	0.57771623	84,45,41,86	0.7138494,0.13257795,0.025764211,0.12780843	-	IRS
82	7	0.50320452	84,45,80	0.68588411,0.12856863,0.18554726	-	IRS
83	7	1	83	1	1	CRS
84	9	1	84	1	16	CRS
85	8	1	18	1	-	CRS
86	8	1	86	1	42	CRS
87	8	1	24	1	-	CRS
88	6	0.42847891	86,16,104	0.31512447,0.22062465,0.46425087	-	IRS
89	10	0.62129719	80,22,104	0.53854885,0.16563114,0.29582001	-	IRS
90	8	1	20,18	0.61783439,0.38216561	-	CRS
91	8	1	18	1	-	CRS
92	5	0.35788511	45,26,109,22	0.000427051,0.65534205,0.25032435,0.093906552	-	IRS
93	1	0.52152339	26,104,109,22	0.33497209,0.096647192,0.21484632,0.3535344	-	IRS
94	9	0.68987501	20,26,18	0.20437245,0.66429769,0.13132985	-	IRS
95	8	1	18	1	-	CRS
96	3	0.82003173	86,26,22,104	0.26015243,0.5772977,0.038641987,0.12390788	-	IRS
97	2	0.70745959	45,26,86	0.064566952,0.90015272,0.035280331	-	IRS
98	6	0.47513516	20,22,109,104	0.2651239,0.083921074,0.52929353,0.12166149	-	IRS
99	9	0.86820806	86,26,22,104	0.038505744,0.32185899,0.10415563,0.53547964	-	IRS
100	3	0.25199846	20,86,104	0.25199846,0.65086856,0.097132974	-	IRS
101	9	0.87979115	20,22,104	0.065248965,0.064874019,0.86987702	-	IRS
102	9	0.68117598	86,104	0.43261999,0.56738001	-	IRS
103	9	0.47440186	45,26,20,86,18	0.20090972,0.25562002,0.081537271,0.069068394,0.39286459	-	IRS
104	9	1	104	1	37	CRS
105	9	0.56621046	86,22,104	0.44825687,0.02130912,0.53043401	-	IRS
106	3	0.74787362	84,45,41,86	0.57572404,0.064730252,0.12269533,0.23685037	-	IRS
107	9	0.58849399	86,104	0.5085263,0.4914737	-	IRS
108	9	0.81726094	20,22,109,104	0.04207771,0.29016366,0.25076562,0.41699301	-	IRS
109	2	1	109	1	15	CRS
110	6	0.59255174	45,26,109,22	0.00872763,0.56187674,0.38353157,0.045864059	-	IRS
111	9	0.81142452	86,22,104	0.074247862,0.12988023,0.79587191	-	IRS
112	4	0.36103124	86,22,104	0.003772977,0.44723415,0.54899287	-	IRS
113	2	0.17612853	20,22,109,104	0.021599058,0.8151974,0.073489137,0.089714409	-	IRS
114	2	0.63121715	26,104,109,22	0.49541472,0.15287115,0.18272238,0.16899175	-	IRS
115	7	0.374154	84,45,41	0.75772983,0.20365262,0.03861755	-	IRS

Table 32: Reference Set, Peer Weight, Peer Count, and Classification of All 115 DMUs After Applying Super-efficiency.

DMUs	PSCs	Efficiency	Reference Set (Efficient DMUs number)	Peer Weight (Lambdas)	Peer Count	Classification
1	2	0.37047866	84,18,41	0.51716649,0.37047866,0.11235486	-	IRS
2	6	0.53481983	26,104,109,22	0.25333833,0.13750643,0.42725536,0.18189988	-	IRS
3	7	0.56055283	20,109,104	0.089943553,0.7598555,0.15020095	-	IRS
4	2	0.99369193	86,26,109	0.13781283,0.22271624,0.63947093	1	IRS
5	5	0.44884999	22,109,104	0.25824888,0.56042054,0.18133058	-	IRS
6	7	0.49159373	86,26	0.07822104,0.92177896	-	IRS
7	2	0.73559787	45,26,86	0.014176412,0.94811468,0.037708913	-	IRS
8	8	1	18	1	-	CRS
9	3	0.70605276	86,26,22,104	0.17991818,0.005377071,0.22780253,0.58690222	-	IRS
10	10	0.20650682	20,26,86,104	0.20650682,0.002264888,0.27546761,0.51576069	-	IRS
11	8	1	18	1	-	CRS
12	9	0.87392301	84,26,45,86	0.13965811,0.70624827,0.020177068,0.13391655	-	IRS
13	2	0.52225037	45,26,18	0.007132385,0.50035329,0.49251433	-	IRS
14	8	1	20,22	0.19736842,0.80263158	-	CRS
15	2	0.27492907	45,18,41	0.40645232,0.27492907,0.31861861	-	IRS
16	8	1	20,18	0.025477709,0.97452229	-	CRS
17	8	1	18	1	-	CRS
18	8	4.92055	24,75	0.47429876,0.52570124	39	CRS
19	8	1	20,18	0.31210191,0.68789809	-	CRS
20	8	1.7	86	1	25	CRS
21	8	1	18	1	-	CRS
22	8	5.3997535	57,109	0.39975311,0.60024689	32	CRS
23	8	1	18	1	-	CRS
24	8	1	18	1	2	CRS
25	8	1	18	1	-	CRS
26	9	1.1322636	84,45,86	0.79086679,0.13440915, 0.074724063	36	CRS
27	6	0.3276777	20,26,18,86	0.063022726,0.6111437,0.26465497,0.0611786	-	IRS
28	10	0.66201662	84,80,18	0.57079399,0.21393703,0.21526898	-	IRS
29	8	1	24,18	0.14545454,0.85454546	-	CRS
30	8	1	18	1	-	CRS
31	7	0.84328033	84,45,80	0.2345336,0.023158974,0.74230742	-	IRS
32	3	0.41663489	20,86,104	0.41663489,0.28255179,0.30081332	-	IRS
33	10	0.20650682	20,26,86,104	0.20650682,0.002264888,0.27546761,0.51576069	-	IRS
34	8	1	18	1	-	CRS
35	8	1	86,41	0.71626298,0.28373702	1	CRS
36	5	0.40122734	86,26,104	0.33716843,0.1292101,0.53362145	-	IRS
37	8	1	20,18	0.012738854,0.98726115	-	CRS
38	2	0.59335672	45,26,22,86	0.015443781,0.84648721,0.13241236,0.005656642	-	IRS
39	7	0.39803553	86,26	0.085253302,0.9147467	-	IRS
40	2	0.87347816	26,109,104	0.28041201,0.45007301,0.26951498	-	IRS
41	8	1.306763	86,42	0.98803872,0.011961279	10	CRS
42	9	1	84	1	2	CRS
43	10	0.40999737	80,22,104	0.42891541,0.26285966,0.30822493	-	IRS
44	6	0.59054233	86,26	0.21847034,0.78152966	-	IRS
45	3	1.2853258	26,80	0.92817411,0.071825888	23	CRS
46	2	0.61392984	86,26	0.19374682,0.80625318	-	IRS
47	10	0.80579527	45,26,80	0.019475547,0.077394584,0.90312987	-	IRS
48	9	0.74147996	20,22,104	0.11946719,,0.16037409,0.72015872	-	IRS
49	10	0.14632709	45,20,86	0.51207802,0.14632709,0.34159489	-	IRS
50	7	0.5620658	84,80,18	0.46881456,0.37493502,0.15625042	-	IRS
51	1	0.36096889	20,86,104	0.36096889,0.17655932,0.46247179	-	IRS
52	8	1	18	1	-	CRS
53	3	0.80681012	84,18	0.68857009,0.31142991	-	IRS

Table 32: Reference Set, Peer Weight, Peer Count, and Classification of All 115 DMUs After Applying Super-efficiency.

54	7	0.17512331	84,86,18,41	0.42254918,0.38951658,0.17512331,0.012810927	-	IRS
55	4	0.84850463	45,26,109,22	0.022023331,0.65823983,0.033166035,0.2865708	-	IRS
56	3	0.62796032	86,22,104	0.13494544,0.34740588,0.51764868	-	IRS
57	9	0.99443054	26,104,109,22	0.037077433,0.83573775,0.078873382,0.048311438	3	IRS
58	9	0.57679494	86,22,104	0.26732997,0.1907786,0.54189143	-	IRS
59	1	0.71707895	20,104	0.15209368,0.84790632	-	IRS
60	5	0.45543838	84,26,45,80	0.60782398,0.066288128,0.12269898,0.20318891	-	IRS
61	10	0.20353869	20,26,18,86	0.082022798,0.71733384,0.12151589,0.079127478	-	IRS
62	9	0.50110212	22,104	0.54004409,0.45995591	-	IRS
63	3	0.63495079	86,22,104	0.18858683,0.28708391,0.52432926	-	IRS
64	8	1	86,18	0.19852941,0.80147059	-	CRS
65	9	0.90015285	84,45,41	0.81453954,0.087884085,0.097576372	-	IRS
66	2	1	22	1	-	CRS
67	7	0.38917901	84,26,45,86	0.35169438,0.52595904,0.117269,0.005077586	-	IRS
68	9	0.1770921	20,26,18,86	0.16599167,0.10922341,0.011100429,0.71368449	-	IRS
69	3	0.23178621	20,86,104	0.23178621,0.64141539,0.1267984	-	IRS
70	1	0.43720876	86,26,22,104	0.011446232,0.480287,0.36450811,0.14375866	-	IRS
71	8	1	18	1	-	CRS
72	8	1	18	1	-	CRS
73	8	1	20,18	0.84076433,0.15923567	-	CRS
74	9	0.20402824	45,86,18,41	0.15847657,0.4908072,0.20402824,0.14668799	-	IRS
75	1	1	18	1	1	CRS
76	8	1	86	1	-	CRS
77	8	1	86,22	0.41984732,0.5815268	-	CRS
78	8	1	18	1	-	CRS
79	10	0.43702871	84,80,18	0.075254492,0.54255714,0.38218837	-	IRS
80	7	1.5294118	47	1	11	CRS
81	1	0.57771623	84,45,41,86	0.7138494,0.13257795,0.025764211,0.12780843	-	IRS
82	7	0.50320452	84,45,80	0.68588411,0.12856863,0.18554726	-	IRS
83	7	1.2086956	80,18	0.013043476, 0.98695652	-	CRS
84	9	1.0827967	26,42	0.1324747, 0.8675253	17	CRS
85	8	1	18	1	-	CRS
86	8	3.7112112	45,35,41	0.11368925,0.61062187,0.27568888	46	CRS
87	8	1	18	1	-	CRS
88	6	0.42847891	86,16,104	0.31512447,0.22062465,0.46425087	-	IRS
89	10	0.62129719	80,22,104	0.53854885,0.16563114,0.29582001	-	IRS
90	8	1	20,18	0.61783439,0.38216561	-	CRS
91	8	1	18	1	-	CRS
92	5	0.35788511	45,26,109,22	0.000427051,0.65534205,0.25032435,0.093906552	-	IRS
93	1	0.52152339	26,104,109,22	0.33497209,0.096647192,0.21484632,0.3535344	-	IRS
94	9	0.68987501	20,26,18	0.20437245,0.66429769,0.13132985	-	IRS
95	8	1	18	1	-	CRS
96	3	0.82003173	86,26,22,104	0.26015243,0.5772977,0.038641987,0.12390788	-	IRS
97	2	0.70745959	45,26,86	0.064566952,0.90015272,0.035280331	-	IRS
98	6	0.47513516	20,22,109,104	0.2651239,0.083921074,0.52929353,0.12166149	-	IRS
99	9	0.86820806	86,26,22,104	0.038505744,0.32185899,0.10415563,0.53547964	-	IRS
100	3	0.25199846	20,86,104	0.25199846,0.65086856,0.097132974	-	IRS
101	9	0.87979115	20,22,104	0.065248965,0.064874019,0.86987702	-	IRS
102	9	0.68117598	86,104	0.43261999,0.56738001	-	IRS
103	9	0.47440186	45,26,20,86,18	0.20090972,0.25562002,0.081537271,0.069068394,0.39286459	-	IRS
104	9	1.8571432	57	1	36	CRS
105	9	0.56621046	86,22,104	0.44825687,0.02130912,0.53043401	-	IRS
106	3	0.74787362	84,45,41,86	0.57572404,0.064730252,0.12269533,0.23685037	-	IRS
107	9	0.58849399	86,104	0.5085263,0.4914737	-	IRS
108	9	0.81726094	20,22,109,104	0.04207771,0.29016366,0.25076562,0.41699301	-	IRS
109	2	1.0958577	57,22,4	0.50060778,0.27480988,0.22458234	15	CRS
110	6	0.59255174	45,26,109,22	0.00872763,0.56187674,0.38353157,0.045864059	-	IRS
111	9	0.81142452	86,22,104	0.074247862,0.12988023,0.79587191	-	IRS
112	4	0.36103124	86,22,104	0.003772977,0.44723415,0.54899287	-	IRS
113	2	0.17612853	20,22,109,104	0.021599058,0.8151974,0.073489137,0.089714409	-	IRS
114	2	0.63121715	26,104,109,22	0.49541472,0.15287115,0.18272238,0.16899175	-	IRS
115	7	0.374154	84,45,41	0.75772983,0.20365262,0.03861755	-	IRS

Table 33: Reference Set, Peer Weight, Peer Count, and Classification of Six DMUs in VRS and Super-efficiency Input-oriented During 2018-2019 and 2020-2021 in the Second Scenario

	DMUs	Efficiency	Reference Set (Efficient DMUs Number)	Peer Weight (Lambdas)	Peer Count	Classification	Ranking
VRS-2018-2019	1	0.55	6,3	0.4,0.6	-	IRS	2
	2	1	2	1	1	CRS	1
	3	1	3	1	2	CRS	1
	4	1	4	1	1	CRS	1
	5	1	5	1	1	CRS	1
	6	1	6	1	2	CRS	1
VRS-2018-2019-Super-efficiency	1	0.55	6,3	0.4,0.6	-	IRS	6
	2	1.4117538	6,3	0.6,0.3	1	IRS	4
	3	2.2647356	6,2	0.1,0.8	4	IRS	2
	4	1.2955651	6,3	0.4,0.6	1	IRS	5
	5	Infeasible	Infeasible	Infeasible	-	IRS	1
	6	1.8477036	4,5,3	0.4,0.3,0.2	4	IRS	3
VRS-2020-2021	1	1	1	1	1	CRS	1
	2	1	2	1	3	CRS	1
	3	0.94192877	4,2	0.3,0.6	-	IRS	2
	4	1	4	1	3	CRS	1
	5	1	5	1	2	CRS	1
	6	0.8992828	5,4,2	0.06,0.01,0.9	-	IRS	3
VRS-2020-2021-Super-efficiency	1	1.1666667	4,2	0.1,0.8	2	IRS	4
	2	1.6349027	3,1,6	0.3,0.06,0.5	3	IRS	3
	3	0.94192877	4,2	0.3,0.6	1	IRS	5
	4	3	5,1	0.9,0.09	3	IRS	2
	5	Infeasible	infeasible	infeasible	-	IRS	1
	6	0.8992828	5,4,2	0.06,0.01,0.9	1	IRS	6

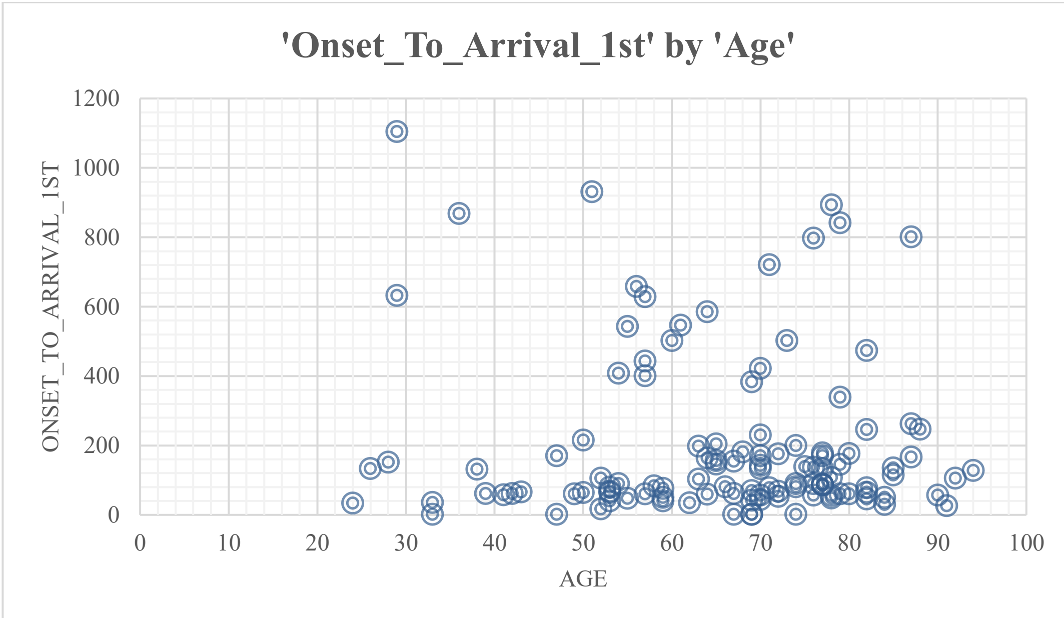

Figure 11: The Relationship Between Onset_To_Arrival_1st to Age.

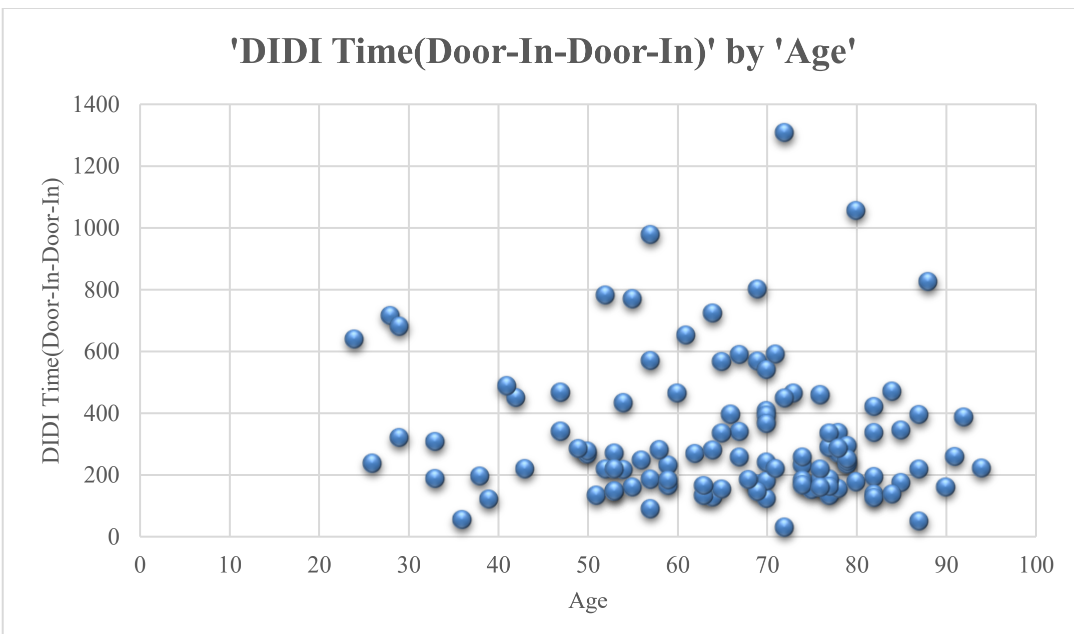

Figure 12: The Relationship Between DIDI Time(Door-In-Door-In) to Age.

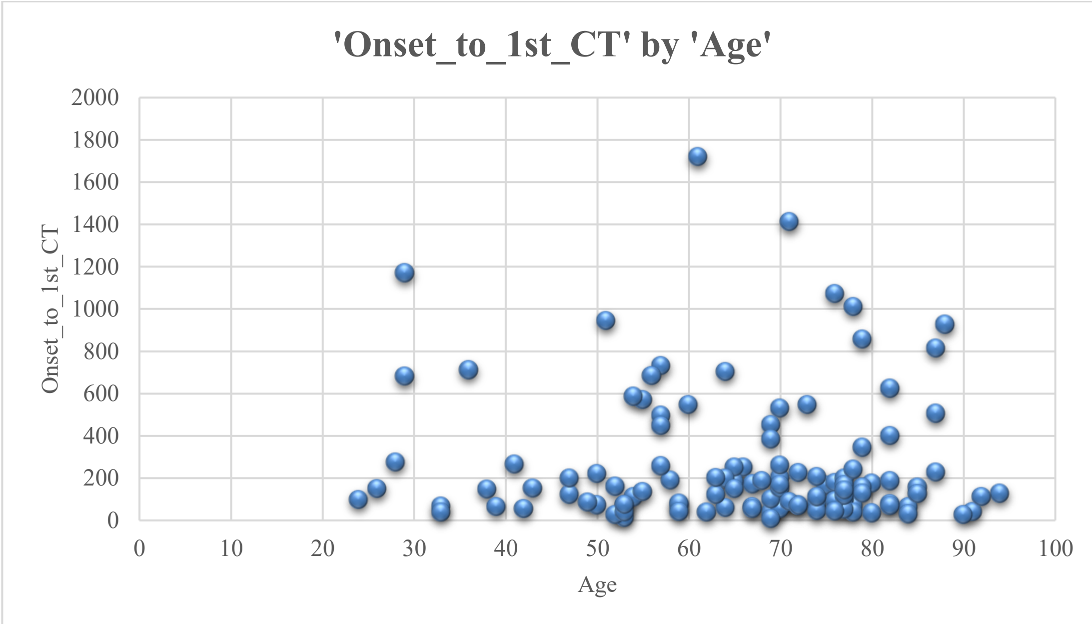

Figure 13: The Relationship Between Onset_to_1st_CT to Age.

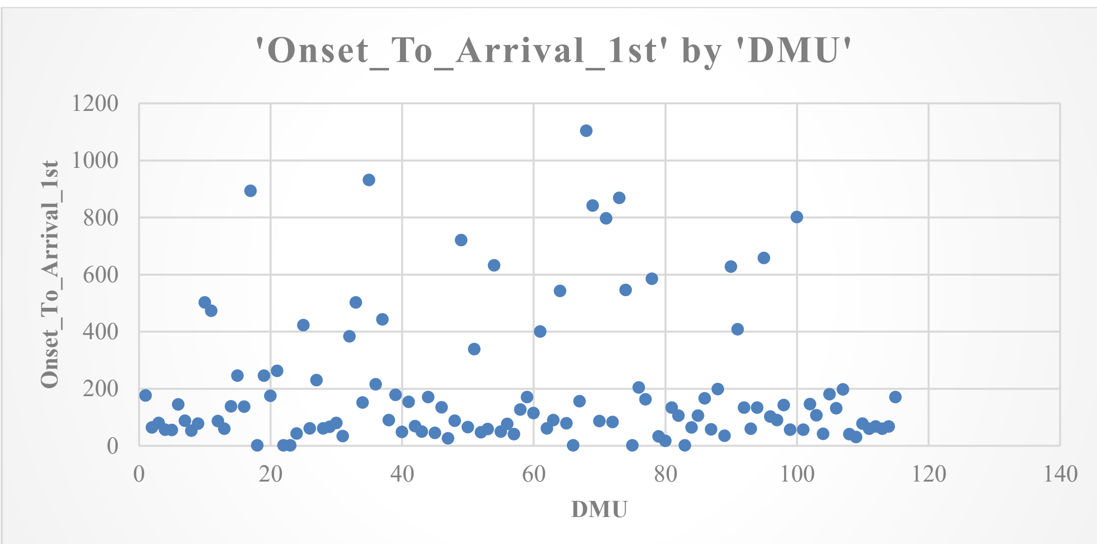

Figure 14: The Relationship Between Onset_To_Arrival_1st to DMUs.

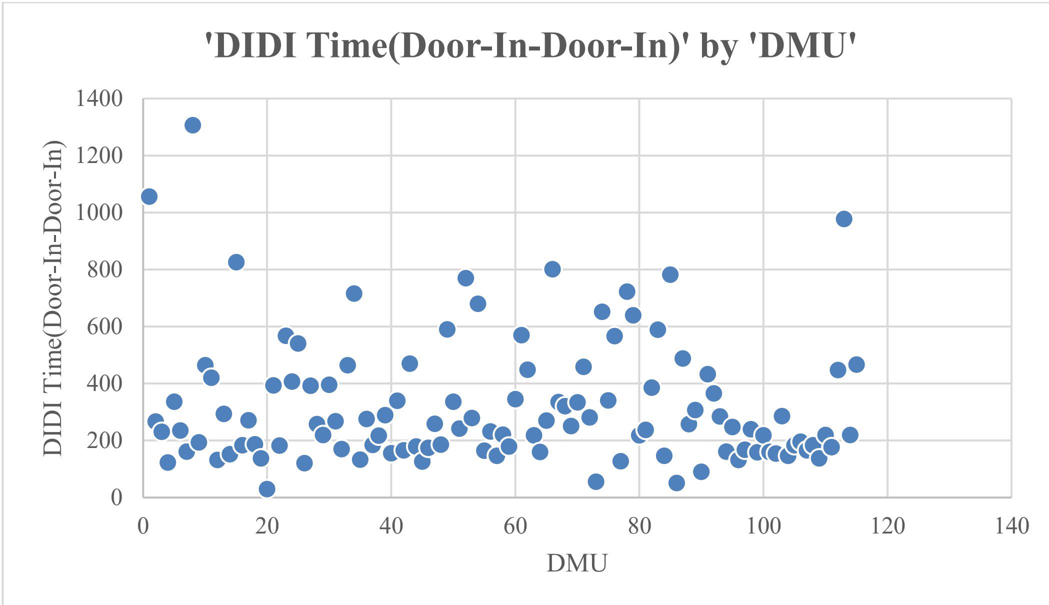

Figure 15: The Relationship Between DIDI Time(Door-In-Door-In) to DMUs.

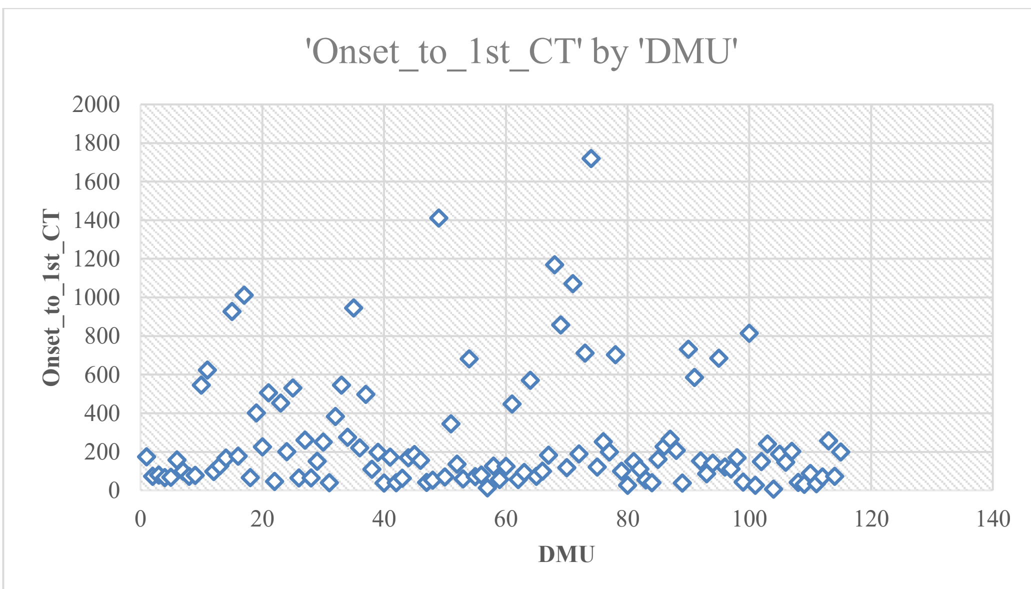

Figure 16: The Relationship Between Onset_to_1st_CT to DMUs.

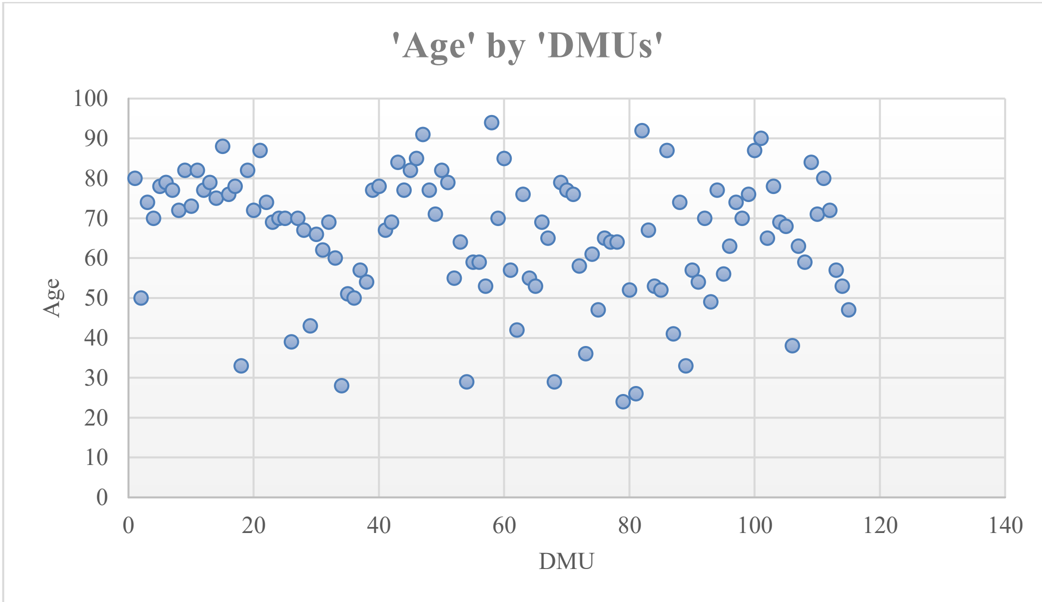

Figure 17: The Relationship Between Age to DMUs.