Improving Effectiveness and Equity of Healthcare Delivery through Systems Optimization

Xiaonan Sun

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2024

Reading Committee:

Shan Liu, Chair

Rebecca G. Maine

John Youngjun Choe

Program Authorized to Offer Degree:

Industrial and Systems Engineering

University of Washington

Abstract

Improving Effectiveness and Equity of Healthcare Delivery
through Systems Optimization

Xiaonan Sun

Chair of the Supervisory Committee:
Associate Professor Shan Liu
Department of Industrial and Systems Engineering

Effective and equitable healthcare delivery is crucial for advancing health outcomes, reducing resource waste, alleviating healthcare disparities, and improving overall individual well-being and community welfare. With increasing costs, limited resources, growing demand for patient-centered services, and advancements in remote technology, resource allocation has gained significant attention as a key strategy to optimize care delivery. The objective of this dissertation is to improve the effectiveness and equity of healthcare services through developing decision-analytic, machine learning, and optimization models using patient-level data, with a focus on both remote and in-person healthcare settings.

In remote care settings, we explored how technologies could enhance healthcare resource utilization for chronic disease management. Remote monitoring has emerged as a promising option with high personalization and adaptability. However, the cost-effectiveness of these technologies remained uncertain. We used chronic depression as a case study and evaluated the cost-effectiveness of remote monitoring strategies compared to rule-based follow-up and fixed-frequency follow-up strategies. We developed a decision-analytic Markov-cohort model to simulate disease progression for patients with different risks, incorporating optimal treatment switching. Results showed that remote monitoring technology can be cost-effective and identified requirements for it to work more effectively. It provided a novel assessment frame-

work that can guide the development of emerging technologies and highlighted the bright future of improving care delivery through remote monitoring.

In in-person care settings, we aimed to optimize trauma care delivery, given its critical role in emergency healthcare. We began by investigating the variability in care delivery within statewide trauma systems. Hospitals are designated as trauma centers (TCs) with level I-V, or non-trauma centers (non-TCs), based on their medical and research resources. To explore trauma care delivery patterns and their association with trauma designation levels, we performed three sets of unsupervised clustering analyses on statewide TCs and non-TCs based on hospital features with a focus on surgical care. We found that the resulting clusters only partially aligned with the TC designations, implying not all hospitals with the same TC level provide equivalent care. The results highlight the performance variability and help us better understand trauma system functioning, guiding the subsequent study to optimize the trauma system at the hospital level.

To optimize statewide trauma systems, we developed a systematic framework for improving care quality while addressing population equity. This objective is achieved by establishing and assigning hospital profiles representing performance targets which can be used to guide resource allocation and operational adjustment decisions. While many studies have focused on optimizing emergency transport services, care quality and equity have often been overlooked. Using state data, we established a set of comprehensive trauma care quality metrics for distinct population groups formed by sociodemographic factors and Injury Severity Score (ISS). We then created a quality index to represent trauma care quality accounting for hospital variations using a Principal Component Analysis (PCA) analysis of the quality metrics. Next, we created hospital profiles using a quality index of each population group, which were estimated from data and imputed using a linear mixed-effects model. We formulated a mixed-integer linear program (MILP) to maximize the quality index of targeted population groups under various equity objectives. The model identified optimal hospital profile assignments as proxies for performance targets for the hospitals. These results help identify necessary resources for performance enhancement, guiding hospitals in making targeted improvements to better serve diverse patient populations.

Overall, this dissertation advances healthcare effectiveness and equity by evaluating remote care technologies, uncovering variability in trauma systems, and establishing optimal performance targets for hospital trauma care delivery. Our findings offer actionable guidelines to enhance chronic disease management in remote settings and improve the quality and equity of statewide acute trauma care systems.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Table Number Page

Chapter 1
INTRODUCTION

1.1 Overview

The delivery of effective and equitable healthcare is essential for promoting individual well-being and community welfare [1]. Effective healthcare is defined as providing care that achieves the desired health outcomes for patients and optimizes the use of available resources [2, 3]. Equitable healthcare ensures that all individuals receive fair access to quality care regardless of their socioeconomic status, geographic location, or other personal characteristics [4, 5]. With rising healthcare costs, growing demand for patient-centered services, and technological advancements, healthcare resource allocation has gained significant attention as a key strategy to optimize care delivery [6]. Effective and equitable resource allocation can lead to improved health outcomes, reduced resource waste, and the alleviation of healthcare disparities [7]. However, allocating healthcare resources can pose challenges as resources are often limited, and demand for healthcare services typically exceeds the available supply [8].

Given these challenges, this research focuses on both remote and in-person care settings to address the unique demands and opportunities presented by each. Remote care settings, driven by advances in telehealth and monitoring technologies, have the potential to revolutionize chronic disease management and improve patient outcomes by providing personalized and accessible care [9, 10]. However, the cost-effectiveness and practical implementation of these technologies remain uncertain, necessitating evaluation to ensure they deliver value in resource-limited environments.

In-person care settings, particularly within trauma care systems, present a different set of challenges. Trauma care is a critical component of emergency healthcare, where timely and effective treatment can significantly impact patient outcomes. However, variability in care delivery across trauma centers leads to disparities in the quality of care provided, making it essential to understand these differences and optimize care delivery to ensure equitable access to high-quality care.

One of the key challenges in this context is the handling of detailed patient-level medical data. While this data is essential for personalizing care and making informed decisions, it brings significant difficulties in terms of integration, analysis, and interpretation. Patient-level data often includes complex and heterogeneous information, which presents challenges in standardizing data formats and ensuring interoperability across different systems, such as electronic health records (EHRs), registry dataset, imaging databases, and laboratory information systems [11]. Furthermore, the dynamic nature of patient conditions and treatment variability complicates the analysis, requiring methodologies that can account for these fluctuations and interactions. Existing methodologies often struggle to incorporate the full spectrum of patient variability, treatment effects, and confounding factors, highlighting the need for more robust analytical approaches that can better handle these complexities [12].

Previous studies often rely on single methodologies to address these challenges, which may fall short due to the complexity and multifaceted nature of real-world healthcare settings [13]. For instance, some research might focus exclusively on statistical analyses, which, while providing valuable insights, may not fully capture the dynamic and interactive aspects of healthcare systems. Others may rely solely on optimization models, which can offer solutions to specific resource allocation problems but may not account for the nuanced variations in patient needs and treatment outcomes. Machine learning techniques, while powerful in uncovering patterns from complex datasets, often require integration with other methods to address the full spectrum of healthcare challenges [14]. This reliance on a single approach can limit the ability to address the diverse aspects of healthcare delivery comprehensively.

To overcome these limitations, our research integrates multiple methodologies — combining decision-analytic models, statistical analyses, machine learning, and optimization techniques — to provide a comprehensive analysis. Decision-analytic models offer a structured way to evaluate different healthcare strategies and their outcomes [15]. Statistical analyses help in understanding the variability and relationships within healthcare data [16]. Machine learning techniques can uncover patterns and predict outcomes from complex datasets, enhancing our understanding of patient needs and system performance [14]. Optimization models assist in identifying the optimal guidance of resource allocation to achieve desired outcomes [17]. This integrated approach helps us address the different parts of healthcare delivery and resource allocation more effectively and equitably. By combining the strengths of each method, we can get a better overall understanding of the challenges and find more balanced solutions.

The motivation behind this research is to develop and recommend strategies for guiding healthcare resources more effectively and equitably. This study addresses critical aspects in advancing healthcare delivery, such as evaluating the cost-effectiveness of emerging technologies in remote care settings, understanding the variability in in-person trauma care delivery, and optimizing these systems to reduce disparities in access to high-quality care. By integrating various methods and tackling the complexities of patient-level medical data, this research aims to improve the effectiveness and equity of healthcare delivery. The findings will offer actionable insights and frameworks to enhance chronic disease management, optimize trauma care systems, and ultimately contribute to a healthcare system that better meets the diverse needs of patients and communities.

1.2 Research Objective

The research objective of this dissertation is to develop and recommend strategies to deliver healthcare effectively and equitably. To achieve this goal, we focus on three aims.

(1) Evaluate the cost-effectiveness of remote monitoring technologies for chronic depression compared to rule-based and fixed-frequency follow-up strategies using a methodology framework primarily based on decision-analytic methods.

(2) Identify variations in the delivery of in-person care within statewide trauma systems

and assess its alignment with designated trauma levels through unsupervised clustering analysis.

(3) Enhance trauma care quality and address equity among population groups through a system framework that includes an optimization model to set hospital-level performance targets and guide resource allocation accordingly.

Through these aims, we contribute to provide evidence-based recommendations that guide healthcare providers and policymakers in making informed decisions about resource allocation. This will ultimately improve healthcare delivery in both remote and in-person settings and promote individual and community well-being.

1.3 Organization of Dissertation

The dissertation proposal is organized into three main sections, each corresponding to the above aims. Chapter 2 focuses on the cost-effectiveness evaluation of remote monitoring technologies for chronic depression. Chapter 3 examines the variability in in-person care delivery within statewide trauma systems. Chapter 4 enhances trauma care quality and addresses disparities in access to high-quality trauma care among sociodemographic and injury severity groups by establishing hospital performance targets to guide resource allocation. Finally, Chapter 5 summarizes the contribution of this dissertation.

In Chapter 2, we focus on remote care settings. The chapter investigates how emerging technologies can enhance healthcare delivery for chronic disease management. Using chronic depression as a case study, the research evaluates the cost-effectiveness of remote monitoring technologies compared to traditional follow-up strategies. A decision-analytic Markov-cohort model is employed to simulate disease progression with treatment switches and assess the impacts of different monitoring strategies. The findings suggest that remote monitoring technologies can be both cost-effective and potentially cost-saving, especially in high-risk scenarios. The chapter introduces a novel assessment framework that guides the development of these technologies and underscores their potential to transform chronic disease management.

In Chapter 3, we shift focus to in-person care. The chapter explores the variability in trauma care delivery within statewide systems. Trauma centers (TCs) and non-trauma centers (non-TCs) are analyzed using unsupervised clustering methods to identify patterns and discrepancies in care. The research reveals that while some alignment exists between trauma center designations and hospital performance clusters, significant variability remains. This suggests that current designation systems do not fully capture the nuances of care provided. By classifying surgical procedures, integrating procedure complexity, and combining various care features, the study offers a new framework for understanding trauma system functions, suggesting a targeted approach to optimizing trauma systems at the hospital level.

In Chapter 4, we develop a systematic framework to optimize statewide trauma systems with a focus on both care quality and equity. The framework includes an optimization model designed to set performance targets at the hospital level and guide resource allocation. This model considers population groups defined by sociodemographic factors and Injury Severity Scores (ISS). It employs a comprehensive set of trauma care quality metrics to establish a quality index, which accounts for hospital variations and measures care performance. The mixed-integer linear programming (MILP) model evaluates various equity-focused objectives, balancing overall performance improvements with enhancements for the most disadvantaged groups. The results offer actionable insights for optimizing resource use and improving trauma care delivery, providing a practical solution for enhancing hospital performance and addressing disparities.

In Chapter 5, we summarize the contribution of this dissertation. Overall, the dissertation advances healthcare effectiveness and equity by evaluating remote care technologies, uncovering variability in trauma systems, and establishing performance targets for hospital care. The integration of decision-analytic, machine learning, statistical, and optimization models provides valuable guidelines for enhancing chronic disease management and improving trauma care quality and equity. The research offers a comprehensive approach to addressing challenges in healthcare delivery, contributing to a more effective and equitable system.

Chapter 2

COST-EFFECTIVENESS ANALYSIS OF REMOTE MONITORING TECHNOLOGY FOR CHRONIC DEPRESSION USING A DECISION-ANALYTIC METHOD

2.1 Introduction

Recent advances in sensors, smartphones, and wireless networks have enabled a new generation of remote healthcare monitoring technologies that promise to improve patient outcomes [9]. Remote monitoring technology can potentially benefit ongoing mental health treatment with high personalization and adaptability [10]. Examples include monitoring for depression [18] and Alzheimer's disease [19]. Technology has the potential to provide a feasible lower-cost alternative to routine follow-up visits, with fewer constraints on patient scheduling and increased access to on-demand care triggered by sensor devices and provided remotely through telehealth platforms [20]. However, with a wide range of commercial design specifications and intended usage scenarios, the cost-effectiveness of this technology remains uncertain.

In this chapter, we used chronic depression as a case study and explored under what conditions a hypothetical remote monitoring technology can be cost-effective for managing ongoing psychiatric treatment. Depression is a complex and dynamic mental disorder characterized by emotional and physical symptoms that may result in disability, reduced quality of life and productivity, and increased risk of death. In the year 2019, 7.8% of all American adults had at least one major depressive episode, and 4.7% had regular feelings of depression [21,22]. Depression is often unrecognized and untreated, and even once treatment begins it is often difficult to monitor its effectiveness [23]. Treatment guidelines from several medical institutions suggest a follow-up frequency of at least every 12 months for patients on maintenance therapy to prevent the recurrence of major depression, and modifying treatment after a minimum of 4-6 weeks for patients with insufficient response to treatment [24–27]. How to optimally schedule follow-up care for patients with partial response or to prevent relapse remains a significant challenge.

Remote depression monitoring technology can enable personalized interventions by adaptively scheduling follow-up visits, leading to timely treatment modification. For example, a mobile app, text messaging, or website can prompt patients to complete a periodic (often bi-weekly) depression assessment, and a remote licensed therapist can review new symptoms, give feedback, and schedule an in-person follow-up if necessary [28]. The patient's health data are continuously collected to develop a personalized depression trajectory, and deviations can automatically generate an alert [29]. Moreover, digital healthcare platforms can empower patients to monitor their health conditions and enable clinicians to address treatment failures much sooner than fixed-frequency medical follow-up [28]. Research has also suggested that implementing measurement-based care [30], however data are collected, can improve treatment effectiveness for major depression [31].

Cost-effectiveness analysis (CEA) is an economic evaluation tool to systematically investigate the costs and outcomes of comparable healthcare interventions [32, 33]. It provides a way for decision makers to use empirical data to best allocate scarce resources by estimating an incremental cost-effectiveness ratio (ICER) and comparing this ratio to a willingness-to-pay threshold [32, 34]. Combined with decision-analytic models and simulation methods, CEA has been used to evaluate screening and treatment routines for depression [35–37]. It also has been used to assess monitoring strategies for depression [38], diabetes [39], HIV [40], asthma [41], and hypertension [42].

We designed a decision-analytic model to evaluate the cost-effectiveness of remote monitoring technology for optimal depression treatment follow-up. We hypothesized that the technology could schedule a patient's next outpatient visit adaptively by detecting changes in the patient's depression severity. We compared the remote monitoring strategy to four traditional non-remote follow-up strategies. We hope our proposed technology assessment method can be extended to evaluate other remote monitoring technologies in advancing cost-effective chronic diseases and psychiatric services [43].

2.2 Methods

2.2.1 Overview

We established the baseline depression progression of a patient cohort using a data-informed simulation, then simulated chronic depression patients' disease progression for two years with treatment assignment under five monitoring strategies. We developed a decision-analytic Markov-cohort model and calculated the costs and QALYs accordingly. We used R and Python for the analyses.

2.2.2 Patient cohort simulation

The data-informed simulation of depression progression was based on an Electronic Health Record (EHR) dataset [44]. The dataset is drawn from the EHR of four U.S. health systems participating in the Mental Health Research Network (MHRN) (HealthPartners, and the Colorado, Washington, and Southern California regions of Kaiser Permanente). Cohorts are defined by age (base case, 45 years), and sex (base case, 69% female). One of the most common depression severity measurements is the Patient Health Questionnaire-9 (PHQ-9) [45], a self-administrated questionnaire to diagnose depression. PHQ-9 scores range from 0 to 27 with a higher score denoting higher severity. Research has demonstrated that, in addition to making criteria-based diagnoses of depressive disorders, the PHQ-9 is a reliable and valid indicator of depression severity. Its conciseness, combined with these qualities, makes the PHQ-9 a valuable tool in both clinical and research environments [46]. Although it is not perfect, the PHQ-9 is frequently used as the measurement of depression severity in clinical practice guidelines for the management of major depressive disorder [26]. The EHR dataset includes longitudinal PHQ-9 scores between the years 2007 and 2012, it also includes age range, sex, observation time interval, and treatment status.

We selected patients receiving ongoing treatment, which was defined as having had psychotherapy visits in the previous 90 days or filled prescriptions for antidepressants in the previous 180 days. We filtered patients having no fewer than six recorded PHQ-9 scores in an approximately one-year time window. We assigned 12 monthly periods for each patient by dividing their total days into 12 segments and calculated the mean PHQ-9 score for each month. The final dataset contained 444 patients (307 female and 137 male). About 38% of the PHQ-9 scores were missing. We imputed missing data using the Exponential Weighted Moving Average (EWMA) [47] method to obtain all 12 monthly PHQ-9 scores for each patient. We clustered the 444 patients based on their PHQ-9 scores using the k-means clustering method [48]. We converted each patient's 12 PHQ-9 scores into a 12-dimensional vector and clustered based on their Euclidean distances [49]. Clustering results showed three groups: a high-risk group with 128 patients, a medium-risk group with 192 patients, and a low-risk group with 124 patients. We used the Silhouette method to identify the optimal number of clusters, evaluating each object's similarity to its own versus other clusters; while the highest silhouette scores were obtained with two clusters, we chose three clusters to provide deeper insights, as the silhouette scores between two and three were close, and grouping into three risk categories – high-risk, medium-risk, and low-risk – is both functional and intuitive. We used the trajectory in the clusters to simulate the baseline depression progressions for the patients with different severity of depression. We further classified depression severity into three levels based on the PHQ-9 score: healthy (H) with scores from 0 to 4; mild depression (M) with scores from 5 to 9; and moderate and severe depression (S) with scores from 10 to 27 (see Table A.2). The mean trajectory of each risk group is shown in Figure 2.1. Although the trajectory of the high-risk group shows a decreasing trend in PHQ-9 scores, the scores still fall into the S level, thus the patients in this remain at high risk of experiencing severe depression.

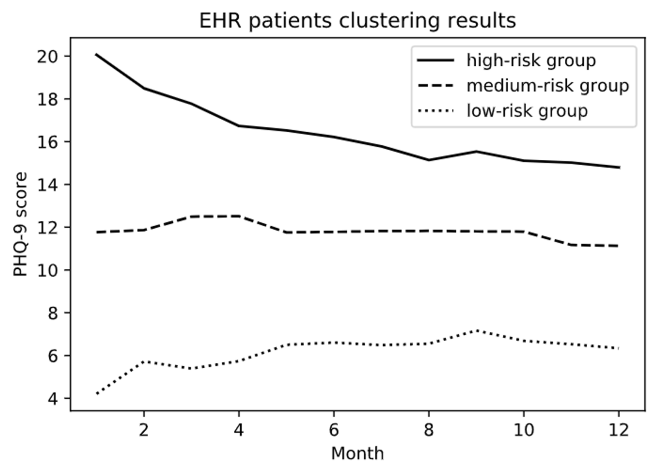


Figure 2.1: The average PHQ-9 score trajectories for each group

2.2.3 Disease progression simulation

We designed a decision-analytic Markov-cohort model with a monthly cycle to simulate chronic depression patients' disease progression for two years. We defined a two-period combined Markov state with the patients' depression level in the last and current month which captures a short-term trajectory that can be used to determine treatment response under an established treatment-switching strategy as shown in Figure A.4. The states include HH, HM, HS, MH, MM, MS, SH, SM, and SS.

PHQ-9 scores greater than or equal to 10 have been found to be 88% sensitive and 88% specific for detecting major depression [45]. Response to treatment is defined as a PHQ-9 score improvement of greater than 50% from baseline, and remission is defined as a PHQ-9 score of less than 5 maintained for at least one month [26]. Based on these definitions: HM, MM, HS, MS, and SS are interpreted as non-response or relapse because these states represent staying in groups with scores of 5 or above (M or S) or moving to a worse level from t-1 period to t period. HH, MH, SH, and SM show treatment responses because they involve remaining at or moving to a healthier level. Response states are further classified in two ways: 1) HH, MH, and SH stand for remission in which a patient has a PHQ-9 score less than 5 for at least one month; SM stands for a response without remission with some improvement in PHQ-9 score; 2) SH and SM stand for unstable improvement since the patient is in S at the previous month; HH and MH stand for stable remission, in which a patient maintains a PHQ-9 score less than 10 for at least two months. We also assume that patients can die in any period regardless of their depression level.

Feasible state transitions are shown in Figure A.4. The Markov state-transition diagram is shown in Figure A.5. We estimated the baseline transition matrix based on numerical frequencies, counting all the transitions in the imputed EHR dataset and calculated the transition probability from state a to state b [50]. We estimated three separate transition matrices for the three risk groups (see Tables A.3 to A.5).

2.2.4 Treatment assignment simulation

A traditional follow-up involves an outpatient clinical visit with the chance to change treatment. Remote monitoring indicates assessing depression severity remotely, triggering a visit for assessment and possible treatment change only when needed. We simulated nine treatment lines in total [51]. A treatment line can consist of antidepressants alone or in a combination with psychotherapy. Patients who failed to respond to the current treatment or relapsed can change to the next treatment line at each scheduled follow-up; these include patients who are in the HM, MM, HS, MS, or SS state. We modeled the treatment effect to be a one-period boost in health [52], represented by an increased probability of transitioning to a healthier state. Specifically, at the time of a treatment change, patients receive an additional probability [51] of transitioning to an H state in the current period (remission) compared to the baseline trasition; and an additional probability [51] of transitioning to an improved state in the current period. For example, at a follow-up point, a patient in the SS state may move to SH or move to SM. If the remission rate of that treatment line is pr_{rm}, the response (excluding remission rate) is pr_{rsp}, and the original proportion of state SS is p_{ss}, then after the treatment boost, a proportion of $pr_{rm} \times p_{ss}$ of the cohort will transition to state SH, and a proportion of $pr_{rsp} \times p_{ss}$ will transition to state SM. Afterward, the patient reverts to the baseline transition matrix until the next treatment change. To leave sufficient time for treatment response, per consensus guidelines for treatment of depression, there are no consecutive treatment changes in two months in our simulation [51, 53]. We assumed if a patient fails all nine treatment lines, then he/she receives no more health boost from treatment and returns to their baseline progression.

2.2.5 Decision-analytic model

We compared five strategies: 1) Adaptive remote monitoring technology with a false negative rate of missing the next needed follow-up and a false positive rate of an unnecessary follow-up. A perfect adaptive monitoring technology with 100% sensitivity and 100% specificity can immediately follow up patients in the nonresponse or relapse states who need a treatment change; 2) Rule-based follow-up strategy, which assigns a follow-up in two months for patients in states HM, MM, HS, MS, or SS; in four months for patients in state SH or SM; in six months for patients in state HH or MH. 3-5) Fixed-frequency follow-up strategy regardless of patients' health states. We evaluated the fixed two-month, four-month, and six-month follow-ups. After exhausting all nine treatment lines, patients in the rule-based and fixed-frequency strategies are assigned a six-month follow-up frequency [24–27]. Remote monitoring patients who exhaust all nine treatment lines are assumed to continue monthly monitoring with no scheduled follow-up. We focused the investigation on how cost-effective the remote monitoring technology is compared to the rule-based follow-up strategy, which is the closest to the current practice according to the depression guidelines [24–27].

The initial states of the Markov model are matched with the group-specific initial health state distribution using the combination of severity levels in the first and second months in the clustered EHR data as shown in Tables A.6 to A.8. We simulated death at the beginning of each month. If it is not a follow-up month, patients progress according to their group-specific transition matrix. If it is a follow-up month, some patients may drop out of the follow-up. During a follow-up appointment, patients may change treatment. After changing to a new treatment, patients may discontinue the treatment due to adverse events.

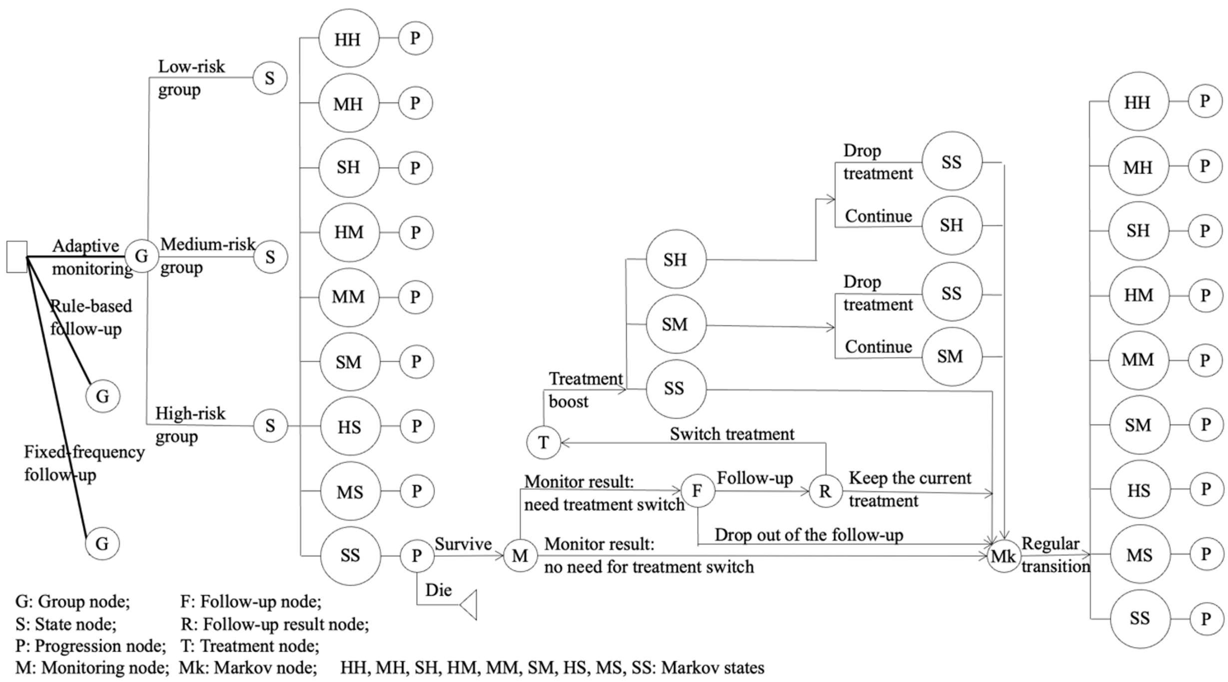


Figure 2.2: Decision-analytic model of depression monitoring and treatment simulation

We assumed it takes some time for the adverse event to happen, thus patients can only discontinue treatment after one month of being on the treatment. The decision-analytic model is shown in Figure 2.2.

2.2.6 Data and sources

Table 2.1 shows model input parameter values. We applied an annual discount rate of 0.03. See Appendix A.1 for detailed explanations.

Table 2.1: Model input parameter values

Variable	Base Case (Range)	Reference
General input		

Annual discount rate	0.03	[54]
Cohort characteristics		
Age	45 (30-64)	EHR [44]
Sex		
Female	0.69	EHR [44]
Male	0.31	EHR [44]
Annual background death probability		
Age 45	0.00225	[55] *
The mortality hazard ratio		
Severe depression (S)	1.59 (1.113-2.067)	[56]
Moderate depression (M)	1.52 (1.064-1.976)	[56]
Minimal depression (H)	1.45 (1.015-1.885)	[56]
Annual probability of follow-up discontinuation **	0.211 (0.069-0.309)	[51,57]
Remote monitoring technology		
Sensitivity	0.76 (0.64-0.95)	[44]
Specificity	0.74 (0.43-0.82)	[44]
Treatment effectiveness		
Annual probability of treatment discontinuation due to adverse event	0.249 (0.151-0.391)	[51,57]
Remission probability, per month		
Treatment 1-3	0.397 (0.321-0.478)	[51,58]
Treatment 4-6 (relative risk vs. treatment 1)	0.93 (0.86-1.00)	[51,58]
Treatment 7-9 (relative risk vs. treatment 1)	0.77 (0.70-0.85)	[51,58]
After treatment 9	0	[51,58]
Response probability, per month		
Treatment 1-3	0.631 (0.553-0.703)	[51,58]
Treatment 4-6 (relative risk vs. treatment 1)	0.77 (0.73-0.81)	[51,58]
Treatment 7-9 (relative risk vs. treatment 1)	0.48 (0.44-0.53)	[51,58]
After treatment 9	0	[51,58]

Costs, 2023$		
Remote monitoring, per month ***	12 (0-24)	[59, 60]
Follow-up appointment, per time	131 (89-176)	[61]
Background treatment, per month †		
Treatment 1-3	1532 (1435-1628)	[62]
Treatment 4-6	1679 (1526-1831)	[62]
Treatment 7-9	1794 (1557-2030)	[62]
After treatment 9 ‡	1669 (1505-1829)	[62]
Drug, per month	57 (18-147)	[63, 64]
Health utility		
level S §	0.49 (0.46 to 0.53)	[65]
level M	0.62 (0.58 to 0.65)	[65]
level H	0.7 (0.67 to 0.73)	[65]

* Sex difference is considered in the mortality rate and the base case value is weighted by age proportion.

** We computed the annual follow-up discontinuation probability to be the total discontinuation

*** The cost of remote monitoring is designed as a subscription or on-demand call fee, with the follow-up costs listed separately and not included in this remote monitoring cost.

probability subtracted by the drug adverse event discontinuation.

† Background treatment cost includes the drug cost.

‡ The cost after treatment 9 is computed as the average of treatment line 1-9.

§ The utility of level S is the average utility based on the PHQ-9 score range (53).

2.2.7 Analysis

Outcomes include total discounted costs, quality-adjusted life-years (QALYs) gained, and incremental cost-effectiveness ratios (ICERs) of the five strategies. We used the 2023 GDP per capita in the USA, $81,630, as the willingness-to-pay (WTP) threshold [66]. In the base case, we investigated which strategy is cost-effective and found the frontiers among all five strategies in each group. We further carried out sensitivity analysis on technology factors while keeping all other parameters at base case value to investigate under what ranges of sensitivity, specificity, and cost the remote monitoring technology is cost-effective compared to the rule-based strategy. We then kept the sensitivity, specificity, and cost of the remote monitoring technology at base case value and performed a deterministic sensitivity analysis for all the non-technology-related parameters in one-way, two-way, and scenario analyses.

2.3 Results

2.3.1 Base case

The costs, QALYs, and ICERs of the five strategies for each risk group are shown in Tables A.9 to A.11. The adaptive monitoring strategy has an ICER of \$57,901/QALY, \$74,830/QALY, and \$71,545/QALY compared to the next best alternative for the high-risk, medium-risk, and low-risk groups, respectively. For the high-risk group, only the fixed frequency 2-month follow-up strategy has an ICER exceeding \$81,630/QALY. For the medium-risk group, the fixed frequency 6-month, 4-month follow-up, and adaptive technology are not dominated by other strategies (i.e., a strategy with lower QALYs and higher cost compared to another strategy, or a linear combination of other strategies are dominated). For the low-risk group, fixed frequency 2-month is the only dominated strategy by remote monitoring technology. ICER frontiers are shown in Figure 2.3.

2.3.2 Sensitivity analysis of technology factors

We quantified the impact of sensitivity, specificity, and monitoring cost on the cost-effectiveness of adaptive technology compared to the rule-based strategy, which resulted in 11*11*3*3=1089 scenarios as shown in Table A.12. The technology could be: 1) dominated by the rule-based follow-up strategy, which means the QALYs of the technology are less than the QALYs of the rule-based strategy; 2) cost-saving, which means the technology has higher or equal QALYs

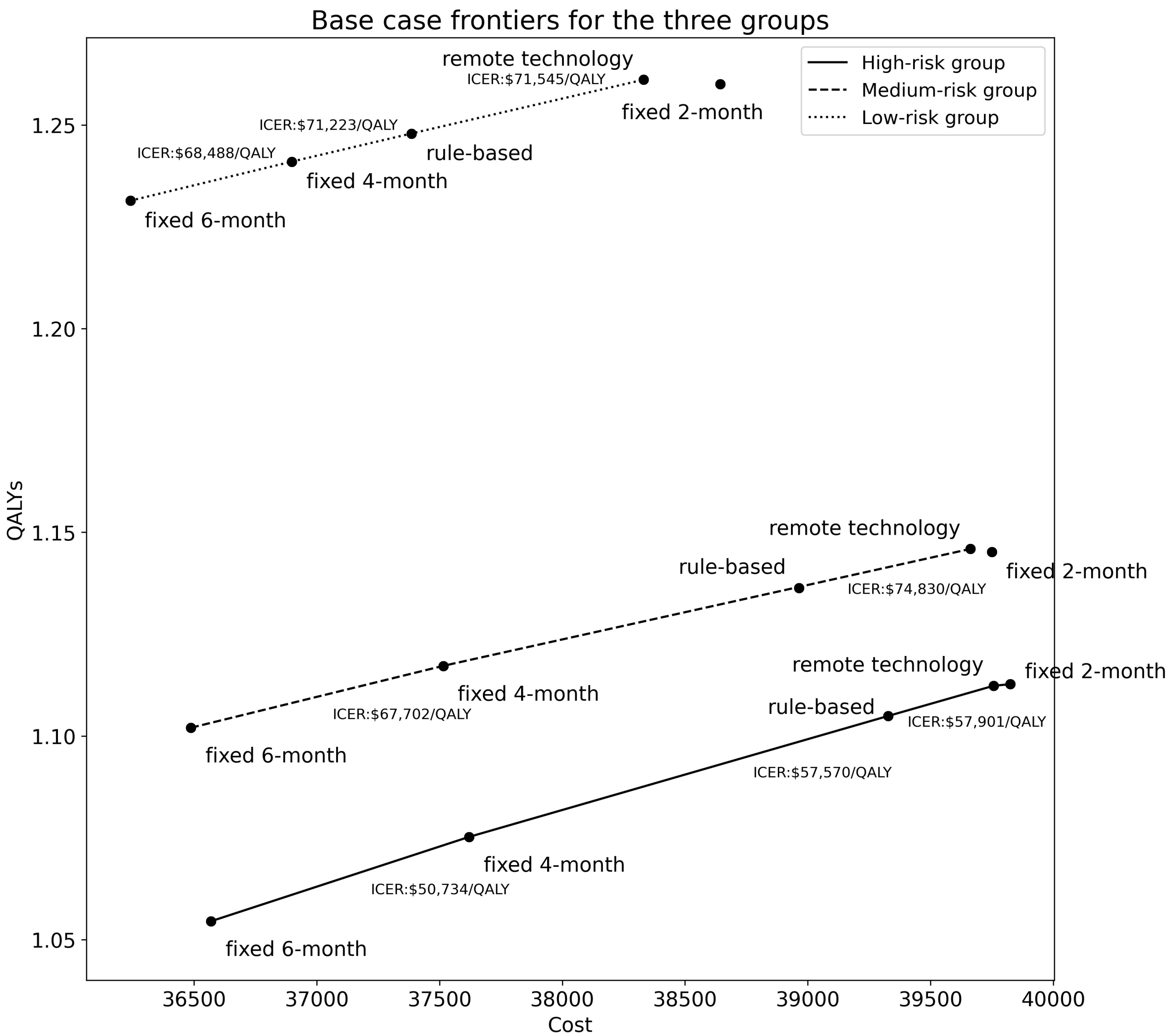


Figure 2.3: Base case cost-effectiveness frontiers for the three risk groups

and a lower cost compared to the rule-based strategy; 3) with an ICER value. We are interested in the regions where the technology could be cost-saving or cost-effective with an ICER below $81,630/QALY.

We used heat maps to show these results (Figure 2.4) for a fixed technology cost of $12 per month. Results for all settings are shown in Figures A.6 to A.14. The heat map is used to visualize data in two dimensions by color intensity [67]. The x-axis shows specificity from 0 to 1, and the y-axis shows sensitivity from 0 to 1. We used the white color to represent the ICER values near the willingness-to-pay threshold of $81,630/QALY. The red color means the ICER is above the threshold, which is not cost-effective; the blue color means the ICER is below the threshold, which stands for cost-effective. Results showed that within the same risk group, once the sensitivity reaches above a certain threshold, the adaptive technology is no longer dominated by the rule-based strategy. In the nondominated region, remote monitoring technology is more cost-effective at higher specificity and lower monitoring costs. Achieving high specificity is more important when the remote monitoring cost is high, and the technology could be cost-saving when the cost is free (or extremely low, see Figures A.6, A.9 and A.12). The increase in cost sharply increases the requirement of sensitivity and specificity for the technology to be cost-effective. Comparing the results of the three groups, the technology required a higher sensitivity for sicker patients to outperform the rule-based strategy and is more cost-effective if it reaches the desired sensitivity in the higher-risk group.

2.3.3 Sensitivity analysis on all parameters

We further performed a deterministic sensitivity analysis for all parameters not related to the technology itself in one-way, two-way, and multi-way analyses (detailed combinations provided in Table A.13). We simulated 291 scenarios in total and 97 scenarios (including the base cases) for each group. For one-way sensitivity analysis (see details in Appendix 2), group difference appears in the follow-up cost: the technology is more cost-effective at a higher follow-up cost in the high-risk group while it is more cost-effective at a lower follow-up cost in the low-risk group. The rule-based strategy assigns very frequent follow-ups for

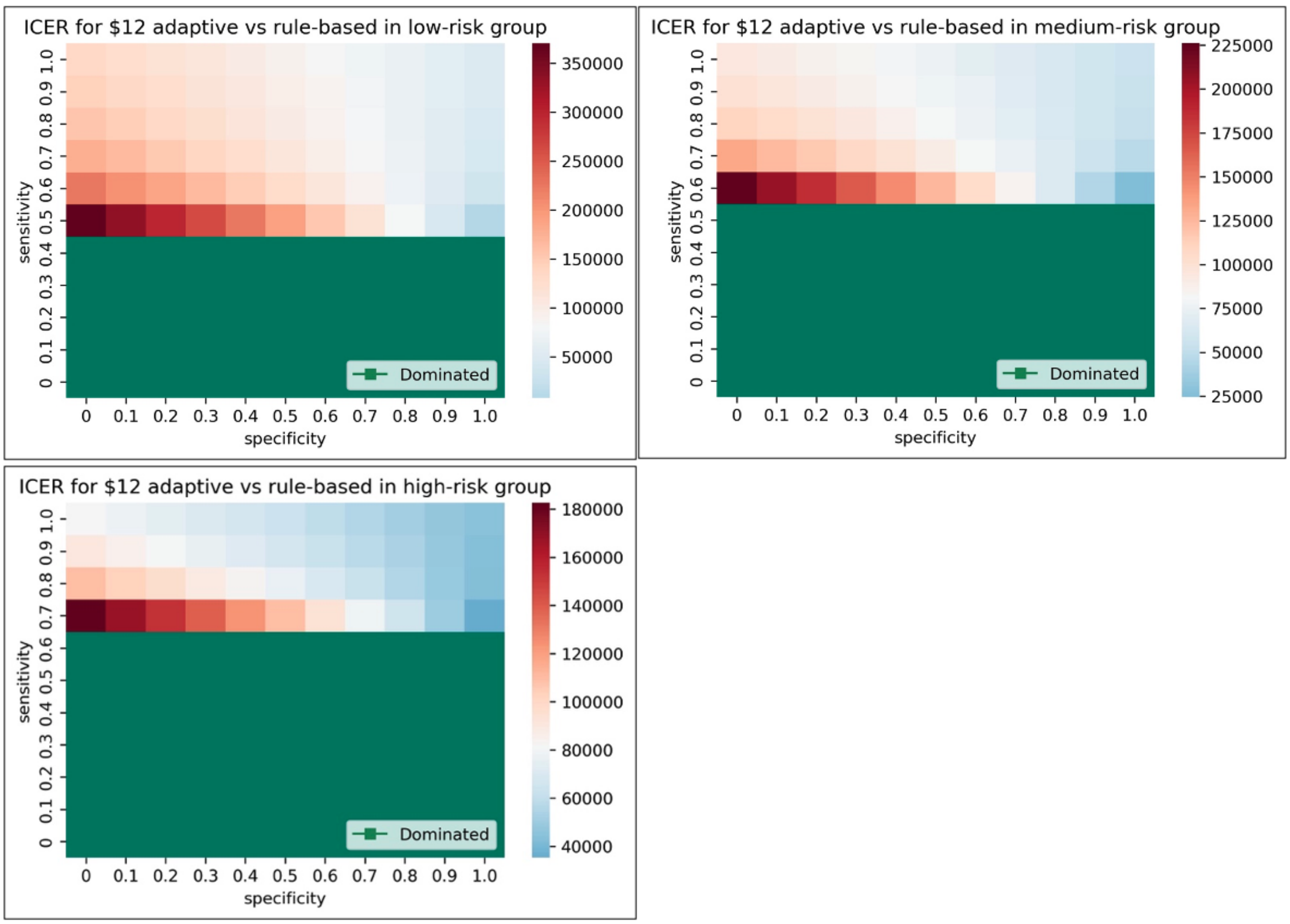


Figure 2.4: ICER for the technology vs rule-based strategy under $12 per month in three groups

high-risk patients, but very few follow-ups for low-risk patients. This result implies that when patients are sicker and need more frequent follow-ups, the rule-based strategy is very aggressive in scheduling, resulting in some unneeded follow-up visits (false positives), and thus remote monitoring becomes more attractive when the cost of follow-up is high. Whereas for the healthier group of patients who do not need frequent follow-up, the remote technology may assign more unnecessary follow-ups while the rule-based strategy is already performing well. Therefore, remote monitoring becomes more attractive under lower follow-up costs compared to rule-based strategy.

The adaptive technology is never dominated or cost-saving for full scenarios sensitivity analysis under all simulated scenarios. It is cost-effective in 74% (72 out of 97) of the scenarios for the high-risk group, 67% (65 out of 97) of the scenarios for the medium-risk group, and 74% (72 out of 97) of the scenarios for the low-risk group. Under various parameter combinations, the significant parameters found in the one-way sensitivity analysis remain the key factors. Thus, we conclude that adaptive remote monitoring technology is generally cost-effective compared to the rule-based strategy and is more robust for high-risk and medium-risk groups. In addition, technology-related factors (cost, sensitivity, and specificity) are the main drivers of cost-effectiveness compared to other treatment and health-service-related parameters.

2.4 Discussion

We assessed the cost-effectiveness of a hypothetical adaptive remote monitoring technology with variable accuracy and cost compared with a rule-based follow-up strategy that is similar to current practice as well as three fixed-frequency follow-up strategies. We simulated a cohort of chronic depression patients undergoing treatment for two years using a decision-analytic Markov-cohort model with nine available treatment lines.

We found the remote monitoring technology is robustly cost-effective with appropriate technology factors: First, for the technology to be not dominated by another strategy, its sensitivity needs to reach a certain threshold, which increases with the patient's baseline risk of severe depression. In addition to reaching a sensitivity threshold, the next priority is to improve specificity. Second, the most cost-effective technology does not align with perfect sensitivity, rather it is at a combination of high sensitivity and perfect specificity where the technology could be cost-saving or very cost-effective. This implies that false positives are very important factors to consider when designing a remote monitoring technology to avoid costly over-intervention. The cost of the technology can be higher only if both sensitivity and specificity are sufficiently high. Third, given high accuracy, the technology can be cost-effective under a variety of disease and treatment conditions. The technology is more cost-effective for sicker patients, lower cost for further treatment lines, higher treatment effectiveness, and poorer quality of life for severe depression. Fourth, patients may benefit more from the technology when the cost of follow-up is high. The technology could potentially fix problems with the financing system that make outpatient follow-up visits too expensive. Please note that our conclusions regarding the cost-effectiveness of remote monitoring technology are based on our chosen willingness-to-pay (WTP) threshold of $81,630, in line with the GDP-based threshold. Different threshold choices may lead to varying conclusions.

Our findings on remote monitoring technologies being generally cost-effective align with previous research on the economic evaluations of remote monitoring strategies for chronic diseases. For example, one study highlighted the cost-effectiveness of telemonitoring for Chronic Obstructive Pulmonary Disease (COPD), showcasing its potential to reduce mortality and healthcare costs [68]. Another study focused on Home Blood Pressure Telemonitoring and Case Management for hypertension care, demonstrating its effectiveness in improving care without increasing overall medical costs [69]. Similarly, a study comparing the costs of home blood pressure telemonitoring with conventional office monitoring found telemonitoring to be more costly but still provided valuable insights into its cost-effectiveness [70]. Additionally, a comparison of telemonitoring versus usual care for uncontrolled blood pressure management revealed that while telemonitoring was more effective, it also incurred higher costs [71]. Furthermore, findings from another study emphasized the cost-effectiveness of remote monitoring for major adverse cardiovascular events in high-risk post-myocardial infarction patients [72].

Overall, these studies collectively support the idea that remote monitoring holds promise as a cost-effective strategy for managing chronic diseases, despite some uncertainties, which aligns with our findings.

Note that patients with more severe depression are likely to have more frequent visits. Therefore, our filtering method which includes only patients with at least 6 PHQ-9 scores in 12 months, may introduce a selection bias in the simulated cohort. Based on our results for the three risk groups, we observed that remote monitoring technology is more cost-effective in the high-risk group. Thus, we infer that the bias from our filtering method is likely to overestimate the cost-effectiveness of the monitoring technology if applied uniformly to all groups. Nonetheless, we believe it is reasonable to focus on patients with more severe depression when discussing the development of technology, as these patients are more critical in chronic disease management.

We considered sensitivity, specificity, and cost as important technology factors in evaluating remote monitoring technologies. However, variations in other technical aspects, such as user interface design, convenience, and patient preference can lead to differences in patient adoption rate even with the same sensitivity and specificity. For example, quality of the user experience can influence the probability of patients discontinuing remote monitoring. While this may not be a direct technological factor, it is a vital design consideration during technology development. We conducted a sensitivity analysis on factors related to discontinuation since an increase in discontinuation rate can be a proxy for poor user experience. Additionally, a more complex mode of administration may result in higher technology costs. We also performed a sensitivity analysis on the cost of the technology which can account for this variability.

The main limitation of this study is our reliance on simulated data. We made many assumptions in our simulated framework, such as how the disease would progress and how treatment would improve health [73]. These assumptions need further validation from clinical trials and observational studies. These assumptions need further validation from clinical trials and observational studies; However, these studies cannot always fully evaluate future possible scenarios and outcomes; they also take a long time and are expensive. Simulations serve to supplement trials and propose potential trial designs. We also assumed the PHQ-9 questionnaire results represent the true health state of the patients, while the sensitivity and specificity of the PHQ-9 questionnaire can be imperfect [74]. We could have incorporated the sensitivity and specificity of the PHQ-9 instrument as two additional parameters in our model. However, since we already modeled the sensitivity and specificity of remote monitoring, adding those of the PHQ-9 would introduce one more layer which may be unnecessarily complex. Therefore, we consolidated them into a single layer of parameters for remote monitoring accuracy. The accuracy of the questionnaire should be taken into consideration in future studies or other gold-standard measurements should be used to represent the true health state.

Our proposed model may be adapted to evaluate the cost-effectiveness of various novel remote monitoring technologies for other psychiatric services. Contributions from our modeling method include: defining a multi-period Markov state to describe health levels that contain enough information to establish a short disease trajectory; deciding on whether the patient needs treatment modification based on the interpretation of the Markov states and establishing a treatment assignment strategy accordingly; using a one-step boost in health levels to simulate treatment effect emphasizing remission and response rates; conducting extensive sensitivity analyses on technology factors to guide technology development requirement. Also, our study used a Markov-cohort model that differentiated patients only into three risk groups. For future research, we could incorporate additional patient characteristics to represent a more diverse population, including various demographic factors. Furthermore, we can explore the integration of personalized prediction models for depression trajectory within the framework to enhance treatment change detection. Additionally, extending the simulation period could enable us to evaluate the long-term cost-effectiveness and sustainability of remote monitoring technologies beyond the two-year timeframe used in the current study.

2.5 Conclusions

This study aims to propose a systematic technology assessment method to guide the development of emerging monitoring technologies used in chronic disease care management through integrated computational tools and decision-analytic modeling. We identified several requirements for remote monitoring technology to be a cost-effective way to deliver chronic depression care services.

Chapter 3

CLUSTERING ANALYSIS OF TRAUMA AND NON-TRAUMA CENTERS USING HOSPITAL FEATURES INCLUDING SURGICAL CARE

3.1 Introduction

Injuries are a major health concern, causing 16,000 deaths per day and over 5 million deaths per year worldwide [75, 76]. In the United States, injury is the primary cause of death for individuals $\leq$ 44 years [75,76]. Trauma systems are an organized, multidisciplinary response to injuries of different severities across a geographic region, and have reduced mortality and improved injury outcomes [77, 78]. Trauma systems aim to deliver timely appropriate care to all injured people within a geographic area. This is achieved by setting standards for the type of injury care different hospitals in the system should provide [79]. In trauma systems, hospitals are designated as trauma centers (TCs) and non-trauma centers (non-TCs). TCs within the United States are verified by the American College of Surgeons (ACS) and/or state departments of health as level I-V based on resources, trauma volume, and educational and research commitment [80]. Level I and level II TCs can provide trauma expertise, subspecialized care, and, frequently, more advanced technology than TCs with lower levels [81]. The key difference between level I and level II TCs is that level I TCs are high-volume teaching hospitals that engage in research and community outreach and serve as leaders within the trauma system [82], while Level II centers provide the same level of care for most injured patients, including the most severely injured, but may not have all highly specialized services and do not necessarily engage in the same research and community outreach [82]. Level III, IV, and V TCs can provide definitive care for more minor injuries, and stabilize severely injured patients and transfer them to higher level TCs if needed [83].

Trauma system development has occurred mainly at the state level, and most states have legislation that designates TCs within the state hospital networks [83]. In Washington State, there is one level I TC, seven level II TCs, 73 lower-level TCs (III-V), and 19 non-TCs [82].

While the designation of TC levels sets rigorous requirements to which the TCs must adhere to ensure injured patients are treated at the most appropriate level of care, detailed trauma care delivery patterns are unexplored at different levels TCs in practice [84]. For example, how the distribution of injuries and associated procedures should vary by TC levels is not specified in current guidelines. In an ideal system, patients would be treated at the lowest TC level that could care for their injury pattern and severity well, however, studies have shown that many patients are transferred for reasons other than medical necessity [85]. This can strain limited resources at higher-level trauma centers, potentially decreasing their ability to care for the most severely injured patients [85, 86]. Demographic characteristics of the patients, staffing issues, and economic factors are cited as reasons apart from medical needs associated with the transfer of injured patients to a higher-level TC [85]. Additional socioeconomic factors, such as payer type, social vulnerability, and area-level deprivation, may account for differences in trauma care within a trauma system [87]. Current trauma guidelines do not outline specific care that each level TC should provide or which injuries are best treated at a given level TC, and few studies have characterized the actual trauma care delivered among TC levels across a system [80, 88]. Thus, gaining a better understanding of the real-life variability in trauma care provided by different level TCs and non-TCs is vital to developing strategies to optimize trauma care in a state or region. Optimally aligning TCs functions with designation level and location could decrease the risk of morbidity and mortality, under-triage, over-triage, and medical resource waste [82].

To explore the role that different level TCs play in a mature trauma system, we evaluated whether hospital features including surgical care delivered for injuries can distinguish hospitals by TC levels. We explored whether a cluster analysis of the TCs/non-TCs using these features would align with TC designation levels. Misalignment between clusters and TC levels would demonstrate variations in the type of care provided among TCs of the same designation level within a trauma system, implying that because of the multiple roles that hospitals play in the health care system, TC designation level may not be the only factor to consider when developing trauma system policies. Without a better understanding of this real-world variability in the delivery of trauma care by different centers, trauma system leaders cannot appropriately plan and allocate resources.

3.2 Methods

3.2.1 Data source

We assembled TC/non-TC features from the hospital discharge dataset in the Comprehensive Hospital Abstract Reporting System (CHARS). CHARS collects information for all inpatient admission for all WA state hospitals [89]. We used the dataset in the year 2016 for this study. We matched hospital names and TC level designations according to the WA State Department of Health Trauma Services' definition to all acute care hospitals [90]. We excluded all rehabilitation units, psychiatric units, and swing-bed units. All acute care hospitals that have not undergone state trauma level verification were considered non-TCs.

3.2.2 Surgical care features

We classified the ICD-10-PCS procedure codes into four categories - minor diagnostic, minor therapeutic, major diagnostic, and major therapeutic, based on the Healthcare Cost and Utilization Product (HCUP) - US [91]. In this study, we only focused on the major therapeutic procedures (MPs), which are procedures typically performed in an operating room and performed for therapeutic reasons (e.g., open fractures fixation) [91] by the Diagnosis Related Group (DRG) [92].

Procedure subgroup

Using the HCUP procedure categories [93] and expert review, we grouped the MPs into six subgroups: General Surgery, Orthopedics, Neurosurgery, Urology, Subspecialty (plastic surgery, obstetrics and gynecology, ophthalmology, etc.), and Other procedures. For similar procedures, we did not distinguish separate laterality (i.e., left or right side) and specific digit information. Because ICD-10 codes do not easily capture procedure complexity, we created procedure complexity groups (PCGs) based on injury and procedure.

Procedure complexity group (PCG)

We assumed a positive correlation between injury severity and procedure complexity; therefore, we linked each procedure to injury severity in the related body region. To start, we generated a list of critical and frequent surgical procedures performed for injuries (see Appendix B.1.1) and categorized ICD-10 procedure codes into each group. We used Abbreviated Injury Scale (AIS) to measure the injury severity of the body region. The AIS is an anatomical-based coding system created by the Association for the Advancement of Automotive Medicine to classify and describe the severity of injuries [94]. AIS scores were generated by the R package used to calculate Injury Severity Score (ISS) [95]. Unconverted diagnosis codes were matched using the American Automotive Association file, when possible [96]. Each procedure during a patient's admission was assigned a PCG in the following format: common procedure category, related body region, and AIS score of the related body region (e.g., Open fixation, Extremities lower, 1).

3.2.3 Other features

Other features include the proportion of patients who were male, median age, whether patients were admitted for trauma, transfer status, insurance payer type, ISS, injury mechanism, and social indices.

Admission type

We classified each admission as trauma or non-trauma using the ICD-10-CM diagnosis codes [97]. Patients with at least one admission diagnosis classified as an injury in the National Trauma Data Standard (NTDS) were considered trauma patients [98]. Non-trauma admissions had no admission diagnoses included in the NTDS.

Transfer type

Admissions were considered transfer-in if the patient was admitted from another acute care facility. Admissions were transfer-out if the patient was discharged to a different acute care facility. See Table B.4 for details of which facilities were included in acute care.

Insurance payer type

We categorized the primary payer as private, low-income, or other payers. Private payers include health maintenance organization, commercial insurance, labor and industries, or health care service contractor. Low-income payers include Medicaid, self-pay, or charity care. The remaining types are other payers, which included Medicare.

Injury severity score (ISS)

ISS is used to assess trauma severity and correlates with mortality, morbidity, and hospitalization time after trauma [99]. We first calculated ISS using the diagnosis codes for all trauma admissions and an ISS calculation R package [95]. Some diagnosis codes could not be converted to ISS components with the R package (Table B.5), potentially underestimating the ISS, thus for some patients this value represents a minimum ISS.

Injury mechanism

We classified the injury mechanism as blunt, penetrating, burn, or other for all trauma admissions by the principal E-Codes [100].

Social indices

To include information about the socioeconomic status of both patients and the areas surrounding the hospital we calculated two separate indices. We used the Social Vulnerability Index (SVI) [101] for patients' home residences, based on zip codes, and Social Deprivation Index (SDI) [102] for hospitals' locations. Appendix B.1.2 contains the calculation details and index mapping.

3.2.4 Analysis

To explore whether care patterns aligned with TC level, we carried out statistical analyses on surgical care for injuries and other features for the hospitals by TC level (Table B.7). We tested whether there is a statistically significant variation for each feature across the TC levels using the chi-square and the Kruskal-Wallis as appropriate by distribution. A p-value ≤ 0.05 was considered significant. For features that included non-median counts, we performed an outlier detection test, and considered values > 1.5 times the interquartile range (IQR) to be significant outliers.

We conducted 3 separate clustering analyses on TCs/non-TCs that performed MPs for trauma care. These three clustering analyses used different characteristics of the hospitals to provide complementary viewpoints on factors associated with different clustering. Hospital features not related to clinical care (i.e. percent of admissions that were for trauma) were consistent across the analyses. Table 3.1 describes the selected features in the three sets of clustering analyses. For each feature used, the percentage of missing values was at most 10% of admissions. All missing values were excluded from the analyses.

Given the number and breadth of procedures performed at each facility and across specialties, in the first analysis we sought to simplify how surgical care was included. In Set 1, we created a surgical care sub-cluster label for each surgical specialty using volumes of all unique MP performed within that specialty. The clustering by specialty identified broad patterns in specialty surgical care and reduced dimensionality. In Set 2 we considered the relative frequency of each PCG separately for TCs/non-TCs that had higher annual volumes for MPs performed for trauma care. We explored whether specific individual procedures contributed to the TCs/non-TCs separation when analyzed with the other hospital features. Detailed features for Set 1 and Set 2 are listed in Table B.6. Finally, to determine whether only the differences in the type of surgical care performed for injuries can distinguish trauma center level, we conducted a third analysis using only the PCGs without other hospital features; resulting in two sub-analyses - surgical care volume clustering (Set 3-1) and surgical care distribution clustering based on MP frequency (Set 3-2). Originally, we had 438 PCGs, which we grouped by body region severity score (major injury: AIS ≥ 2.5; minor injury: AIS < 2.5). We conducted the clustering analysis on these 130 modified PCGs. Instead of exploring how the overall volume of procedures within a specialty distinguishes the TCs/non-TCs as in Set 1, Set 3-1 examined how individual procedure volume impacts the TC/non-TC clusters. Set 3-2 explored whether procedure frequencies influence TC/non-TC separation without other features.

For each clustering analysis, we standardized the included features and conducted Principal Component Analysis (PCA). We selected the top components reaching 90% of the total variation from the PCA [103] and conducted an unsupervised clustering analysis using the Partition Around Medoids (PAM) [104] method. See details in Appendix B.1.3. We summarized the contributing features for each analysis and determined if the clusters aligned with TC level designation.

3.3 Results

In 2016, there were 34,645 trauma admissions and 601,328 non-trauma admissions across all hospitals in WA. Table B.7 shows a summary of surgical care and other hospital features/characteristics for all WA TCs/non-TCs by TC level.

Table 3.1: Associated features in the three sets of clustering analyses

	Set 1	**Set 2**	**Set 3-1**	**Set 3-2**
Name	Surgical care procedure subgroup labels and other features clustering	Surgical care PCG distribution and other features clustering	Surgical care volume clustering	Surgical care distribution clustering
# TC/non-TC included	69	53	53	53
# MP carried out for trauma admissions in 2016 in the TC/non-TC included	≥ 1	≥ 50	≥ 50	≥ 50
Features				
Surgical				
# MP	X	X		
% Subgroup MP	X	X		
# Each PCG			X	
Clustering of # each PCG in Major General Surgery	X			
Clustering of # each PCG in Major Orthopedics	X			
Clustering of # each PCG in Major Neurosurgery	X			
Clustering of # each PCG in Major Urology	X			
Clustering of # each PCG in Major Subspecialty	X			

% Each PCG		X		X
Other	X	X		

Abbreviations: MP (major therapeutic procedures); PCG (Procedure Complexity Group).

3.3.1 Set 1. Surgical care procedure subgroup labels and other features clustering

Of the 69 TC and non-TC that performed at least one MP for a trauma admission in 2016, there were 1 (100%) level I, 7 (100%) level II, 24 (100%) level III, 26 (74%) level IV, 2 (14%) level V TCs and 9 (47%) non-TCs. For the procedure subgroup clustering, we chose the optimal cluster number to be between 3 and 10 clusters (Table B.8). Subgroup clustering results are shown in Figures B.3 to B.7. In each specialty, the level I TC was in its own cluster, and higher-level TCs tend to have a higher volume of procedures. Procedure volume compared to other features primarily distinguished the TCs/non-TCs in each subgroup clustering.

In the combined Set 1 analysis, we kept features that accounted for 90% of the total variance captured by the top 10 principal components (Figure B.8). Comparing the PAM clustering results with the number of clusters ranging from 1 to 10, we chose 10 clusters to obtain a near-optimal clustering performance with the most separation (Figure B.9). Figure 3.1 and Figure 3.2(a) show the visualized clustering results. Table B.9 gives the summary of all the original features that contributed to the clusters. It also highlights the key features that contributed at least 10% of the variation in the top 3 principal components, which themselves explained 60% [105] of the total variance. Table 3.2 presents the summary of these key features. The level I TC was alone in cluster 1, cluster 2 contained only level II TCs, cluster 10 contained only level III TCs, and the other clusters contained a mix of different TC levels. The three pediatric hospitals were in cluster 5. PCG cluster labels from procedure subgroups are the major contributors compared to other features. This implies

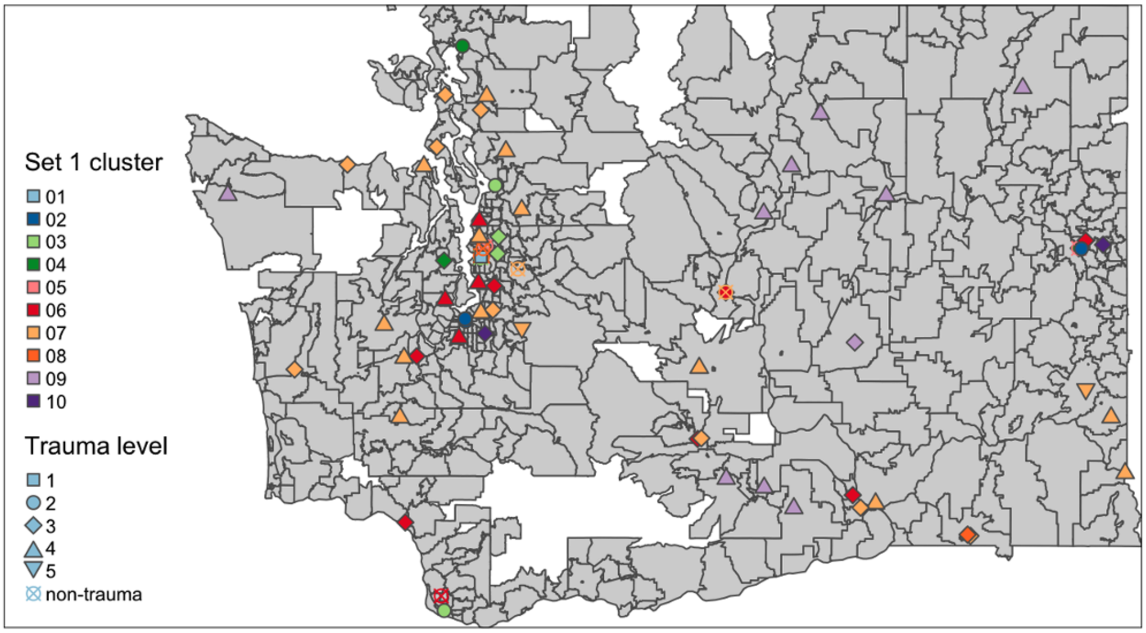


Figure 3.1: Clustering results displayed on a map of WA: Set 1 surgical care procedure subgroup labels and other features clustering

Note: The background of the map illustrates the division of zip codes (which was also used as the division of social indices calculation) within the state of Washington (WA). Each symbol on the map represents a hospital, where the geographic location is indicated by the symbol's placement. The color of the symbol represents the cluster to which the hospital belongs, and the shape denotes the designated trauma level.

that beyond the total volume of surgical care, the volume for each specialty also varies and distinguishes TCs/non-TCs even among hospitals of the same level. For example, Level III TCs in cluster 10 and cluster 8 provided a similar amount of trauma MP of all specialties, while the ones in cluster 10 provided more orthopedic care and less neurosurgery care (see Table B.9).

Table 3.2: Key features contributed to the TCs/non-TCs clusters from Set 1 surgical care procedure subgroup labels and other features clustering

Cluster	1	2	3	4	5	6	7	8	9	10
TC/non-TC levels in the cluster	I	II	II, III, Non	II, III	II, Non	III, IV, Non	III, IV, V, Non	III, Non	III, IV	III
# TC/non-TC in the cluster	1	3	5	3	3	12	26	4	10	2
Cluster mean										
% TC/non-TC in General Surgery label 2[a]	0	100%	80%	100%	0	0	0	75%	0	0
% TC/non-TC in General Surgery label 3[a]	0	0	20%	0	100%	100%	100%	25%	100%	100%
% TC/non-TC in Orthopedics label 2[a,b]	0	100%	100%	100%	0	100%	0	0	0	100%
% TC/non-TC in Orthopedics label 3[a,b]	0	0	0	0	100%	0	100%	100%	100%	0
% TC/non-TC in Neurosurgery label 2[a]	0	100%	100%	0	0	17%	0	75%	0	0
% TC/non-TC in Neurosurgery label 3[a]	0	0	0	100%	100%	83%	100%	25%	100%	100%
% TC/non-TC in Urology label 3[c]	0	0	80%	0	0	0	0	75%	0	100%
% TC/non-TC in Urology label 4[a]	0	0	0	100%	100%	100%	92%	25%	100%	0

a: Features that contribute no less than 10% of the variation within the 1st principal component.

b: Features that contribute no less than 10% of the variation within the 2nd principal component.

c: Features that contribute no less than 10% of the variation within the 3rd principal component.

†: 100% percent of the TCs/non-TCs in cluster 1 are with general surgery label 1.

Abbreviations: TC (Trauma Center); MP (major therapeutic procedures).

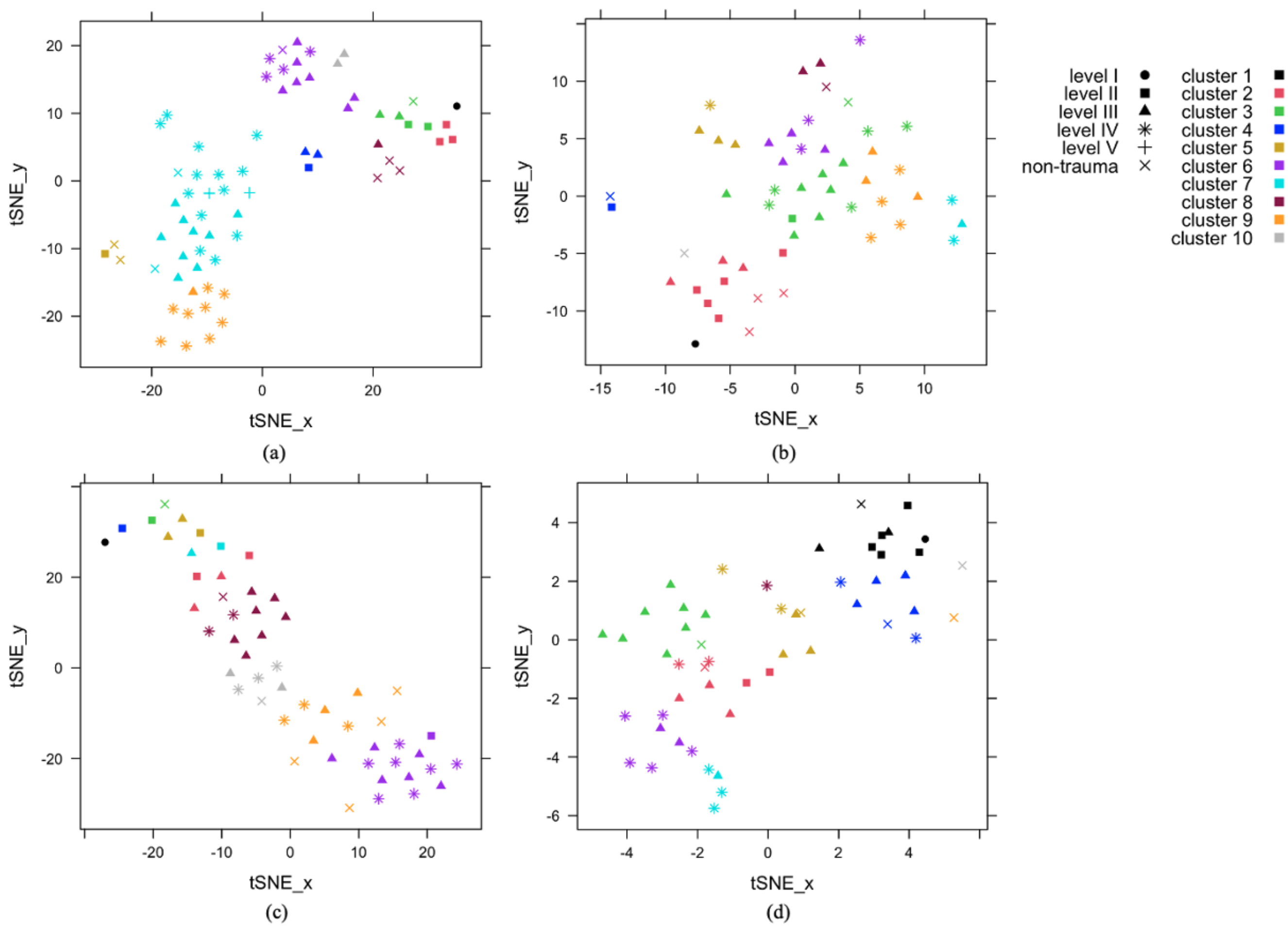


Figure 3.2: Clustering results displayed on a 2-dimensional space: (a) Set 1 surgical specialty procedure subgroup labels and other features clustering, (b) Set 2 surgical care PCG distribution and other features clustering, (c) Set 3-1 surgical care volume clustering, (d) Set 3-2 surgical care distribution clustering

Note: Each symbol represents a hospital, with the distance indicating the relative distances based on all the clustering features. Hospitals with high-dimensional data for all features are visualized using the t-SNE method, which assigns each data point a location in a two-dimensional space, mapping similar data points closely together. Other features include sex, age, admission type, transfer status, insurance payer type, ISS, injury mechanism, and social indices.

3.3.2 Set 2. Surgical care PCG distribution and other features clustering

Of the 53 TC and non-TC that performed $\geq$ 50 MPs for trauma in 2016, there were 1 (100%) level I, 7 (100%) level II, 23 (96%) level III, 15 (43%) level IV, 0 level V, and 7 (37%) non-TCs. The top 9 principal components, which explained 90% of the variance in the PCA, were included (Figure B.11). Comparing the PAM clustering results with the number of clusters ranging from 1 to 10, we also chose 10 clusters (Figure B.12). Figure 3.2(b) and Figure B.10(a) show the visualized clustering results. Table B.10 gives the summary of all the original features that contributed to the clusters, again highlighting the features that contributed at least 10% of the variation within the top 4 principal components, which was the number of principal components that explained 60% [105] of the total variance that drove TC/non-TC separation. Table 3.3 presents the summary focusing only on these key features.

Table 3.3: Original features contributed to the TCs/non-TCs clusters from Set 2 surgical care PCG distribution and other features clustering

Cluster	1	2	3	4	5	6	7	8	9	10
TC/non-TC levels in the cluster	I	II, III, Non	II, III, IV, Non	II, Non	III, IV	III, IV	III, IV	III, Non	III, IV	Non
# TC/non-TC in the cluster	1	11	14	2	4	7	3	3	7	1
Cluster mean										
Median age of trauma patients (year)^b	47	65	72	9	70	71	69	75	74	72

Median age of non-trauma patients (year)[b,c]	55	54	56	6	38	52	60	43	62	66
# Trauma admissions[d]	5605	1042	547	270	434	225	188	784	235	495
SDI in TC/non-TC area[c,d]	74	82	46	62	63	66	56	24	41	61
Mean SVI in trauma patient residence[c]	0.51	0.53	0.5	0.53	0.59	0.66	0.63	0.3	0.43	0.4
Mean SVI in non-trauma patient residence[c]	0.54	0.55	0.51	0.52	0.6	0.66	0.62	0.3	0.45	0.44
% Non-trauma patients with private payer[c]	22%	34%	35%	42%	61%	20%	40%	56%	28%	31%
# Non-trauma MP[d]	8730	11912	4401	4438	3997	1279	3130	8309	1310	11040
% Trauma major Orthopedics in all MP[a]	53%	62%	81%	62%	84%	92%	65%	77%	90%	2%

a: Features that contribute no less than 10% of the variation within the 1st principal component.

b: Features that contribute no less than 10% of the variation within the 2nd principal component.

c: Features that contribute no less than 10% of the variation within the 3rd principal component.

d: Features that contribute no less than 10% of the variation within the 4th principal component.

Abbreviations: TC (Trauma Center); SDI (Social Deprivation Index); SVI (Social Vulnerability Index); MP (major therapeutic procedures); PCG (Procedure Complexity Group).

The result showed that the level I TC was alone in cluster 1, cluster 10 contained only one non-TC, and the other clusters contained a mix of different TC levels. Two pediatric hospitals were in cluster 4. The features that distinguished the clusters were primarily at the hospital level, rather than the specific type of trauma surgeries were performed. Out of all PCGs, only the orthopedic surgical care contributed to the resulting clusters. The nine features that contributed the most to clustering were mean patient age for trauma and non-trauma patients, number of trauma admissions, SDI of the hospital neighborhood, mean patient SVI for trauma and non-trauma patients, payer mix, number of non-trauma operations annually, and percent of trauma operations done for orthopedic injuries. The proportion of all MPs on trauma patients that were for orthopedic injuries contributed the most to the first principal component. Age contributed greatly to the second principal component. Financial and social factors such as the proportion of non-trauma patients with a private payer, age of non-trauma patients, SDI in hospital areas, and SVI in the patient residences all contributed at least 10% to the 3rd principal component. The volume of MPs for non-trauma patients and total trauma admissions contributed the most to the 4th principal component. Several clusters with level II TCs and non-TCs had a higher proportion of younger patients and more private payers. Differences in SDI and SVI separated some of the TCs at the same levels into different clusters; clusters with high SDI did not necessarily have high SVI.

3.3.3 Set 3. Surgical care clustering

The same 53 TCs and non-TCs from Set 2 were used in the Set 3 analysis. For Set 3-1 which only included surgical care volume clustering using PCGs, over 90% of the total variance came from the first principal component (Figure B.13). We chose 10 clusters to be directly comparable to the results from Set 2 (Figure B.14, Figure 3.2(c), Figure B.10(b)). The level I TC was, again, alone in cluster 1. Cluster 2 contained only one level II TC, and all other clusters contained a mix of different TC levels (Table B.11). The TCs/non-TCs are generally separated by the total volume of major procedures conducted, and the clusters with greater total volume MPs also tend to perform a greater volume of each individual PCG. Among all the PCGs, the number of open fixations on the lower extremities contributed the most to the clusters, and the top contributing features were mostly orthopedic.

Rather than absolute volume, Set 3-2 focused on the case mix using the relative frequencies of each PCG for each hospital. In Set 3-2, 90% of the total variance was explained by 10 principal components (Figure B.15). We clustered the 53 TCs and non-TCs into 10 clusters (Figure 3.2(d), Figure B.10(c)). Four procedure groups accounted for at least 10% of the variation within the top 2 principal components, which captured over 60% of the total variance [105] (Table B.12). This was the only analysis in which the level I TC was not in a unique cluster. The level I TC was clustered with eight other TCs and non-TCs including two pediatric hospitals. The major contributing features all belonged to orthopedic care. Level III and level IV TCs varied in terms of the proportion of open fixations on lower extremities with a minor injury, and the cluster containing level I TC had a relatively small proportion of procedures on joints on lower extremities with a minor injury. Surgical procedures on the lower extremities had the greatest influence on the clusters, with the proportion of open fixation on lower extremities with a minor injury being the primary variable in the first principal component. In the second principal component, the four procedures whose relative frequency contributed the most were all on the lower extremities: procedures on the joint in lower extremities with a minor injury, open fixation of a minor injury on lower extremities, and percutaneous fixation of both major and minor injuries in the lower extremities.

3.4 Discussion

To the best of our knowledge, this is the first study attempting to understand the real-life variability of the surgical trauma care provided by different level TCs/non-TCs in a mature trauma system using machine learning applied to both surgical care and hospital-level features derived from patient-level admission and injury data. It highlights the promise of unsupervised machine learning to help trauma system leaders identify the needs and optimize the efficiency of trauma care delivery. In this study, our three cluster analyses of surgical care features and other hospital features found that the clusters only partially aligned with TC designation levels. This demonstrates that though hospitals may have equivalent trauma level designations, their care of injured patients may vary greatly. Given the multiple roles that TC play in providing health care to their communities, this finding is not surprising, however, it has implications for policymakers when considering how to improve trauma systems. The novelty of this work lies in four aspects. First, we classified surgical procedures for injury into novel procedure complexity groups that combined procedures with the injury severity of the body region to approximate the complexity of the procedures, which cannot be determined from ICD-10 codes alone. Second, we explored various ways to combine the surgical care features and other features in different analyses to better understand the relative contribution of each feature type to the clustering result. Third, while most studies investigate the impact of trauma or non-trauma care separately, our study included both trauma and non-trauma care features to evaluate how the mature trauma system functions as a whole. Fourth, we used unsupervised machine learning methods to demonstrate that TCs/non-TCs within the same designation level frequently do not share the same patient characteristics nor do they provide the same mix of surgical care.

Together, these three analyses provide a novel approach to gain insights into the distribution of trauma care in a mature trauma system. Most trauma systems, including in Washington State, are not developed de novo, but rather are built using existing hospitals whose purpose is to provide care for a multitude of problems, not just injuries. In addition, given the location of different centers, the population in the surrounding areas may have different characteristics that also impacted this analysis. Given the TC and non-TC frequently have multiple priorities in providing care for their communities and often have populations with similar characteristics (e.g., lower income, higher rates of uninsurance), it is not surprising that the cluster analysis did not find perfect alignment between hospitals of the same TC level. However, this analysis can provide insights that could help trauma system leaders identify which hospitals may be most easily changed within the trauma system to serve a different role and which hospital and surgical care features may be most important to consider when developing trauma system policies and addressing issues of equity in access to trauma care. First, for hospitals that performed at least one surgery for trauma in a year, the volume and types of surgical care are the primary drivers of the hospital clusters. Second, in the hospitals with higher volumes of operative trauma, the characteristics of the patient population (e.g., age of trauma and non-trauma admissions, payer mix) played a larger role in cluster formation than the specific type of trauma surgery they were performing. Finally, when only operative care was considered at hospitals with higher trauma surgical volumes (Set 3), the two analyses demonstrate that the volume of the procedure rather than the relative proportions of each type of procedure aligns more, though not completely, with TC designation. Set 3-2 used surgical care case mix, and it was the only analysis that did not separate the level I TC into a unique cluster, implying although level I TC conducts a greater volume of surgical procedures, the relative frequency of each PCG does not vary greatly from the other level TCs. Interestingly, the clustering of hospitals varied greatly with the inclusion of different factors, and surgical care was not always the largest contributor to the group differences.

This study included surgical care for both trauma and non-trauma patients as potential factors that would contribute to hospital clusters. We included this because while logically there is a potential relationship between capacity for trauma care and non-trauma conditions at a hospital, it has not been well evaluated in the literature. By including both groups, this analysis provides additional insight into how delivery of other types of surgical care relates to the surgical care for trauma care around the state's trauma system as well as how trauma and non-trauma populations vary across hospitals. The age differences among the trauma patients aligned more with the TC designation compared to non-trauma patients treated at those hospitals. The level I TC served the youngest population, which aligns with previous research that younger people are more prone to have more severe injuries and thus be treated at a higher level of care [106], and that elderly patients are less likely to be transferred to a higher level of care for their injuries [107,108]. Note that little difference is shown in residence SVI for trauma and non-trauma admissions, which was surprising because we anticipated that trauma patients would differ from non-trauma patients since trauma patients frequently come from a wider referral area than other patients treated at the hospital. Some of the trauma centers are also centers of excellence for non-trauma conditions like strokes and myocardial infarctions [109], and the referral of patients from a larger catchment area for these conditions as well may have diminished any expected difference in the groups. In terms of the payer mix among the level III TCs, some have a higher proportion of private or low-income payers for non-trauma patients only, and some have a lower proportion of private and low-income payers for trauma patients only, implying a relatively large proportion of trauma patients are with "other payers" which include Medicare. This analysis suggests that the inclusion of both trauma and non-trauma care are important when analyzing how to improve a trauma system, as non-trauma care also contributes to natural hospital clusters.

An underlying motivation of this work was to explore a means of analyzing a large data set to provide insight into the factors associated with TC level designation across a mature system that can then be used to inform policies to address equity and efficiency in trauma care delivery. We identified that the real-life variabilities in trauma care only partially aligned with the current trauma level designation. The volume of surgical procedures performed, especially orthopedic procedures, contributed to the differences among level III TCs. The payer mix and social index also had an impact, which distinguished the TCs/non-TCs more by the location they serve rather than the designation level. Not surprisingly, SDI for hospitals and the SVI of the patients they treated were correlated. The level II TCs in the area with higher social deprivation tend to have patients living in more vulnerable residences and with a higher proportion of low-income payers compared to the level II TCs in the area with lower social deprivation, which implies patients tend to go to the closest hospital. Previous work has shown that TCs in the area with higher deprivation and vulnerability scores may receive fewer funds due to lower taxes and a less favorable payor mix and therefore have fewer resources, potentially leading to differences in care, outcomes, and efficiency for these centers [110]. This highlights the potential for inequity since patients nationwide may not have equal access to high-quality trauma care services [111]. We also found that while in the majority of the TCs/non-TCs orthopedic surgical care was the largest proportion of overall surgical care, there were some TCs/non-TCs with a relatively small proportion of orthopedic care and a relatively large proportion of neurosurgery care. Trauma systems were developed with existing hospital infrastructures in most states and improving them is challenging because of resource limitations and few tools to guide improvement. To date, the existing tools do not incorporate the complexity of the interactions between multiple parts of the system [112]. This study shows potential directions to optimize trauma system functioning apart from adding new TCs or transport hubs, as machine learning provides insight into which TCs/non-TCs are the best candidates to be designated at a particular level based on the current operative trauma care and hospital features. However, TC designation does not encourage uniformity and homogeneity; its designation standards are meant to ensure a minimum standard. Beyond this standard, healthcare centers can innovate and adjust the care they provide using their available resources. This flexibility could be essential for hospitals to manage in the current economic situation. In this context, our study can be a valuable tool for understanding these variations, going beyond just focusing on allocation strategies.

This study has several limitations. Access to more recent state data was limited during COVID because of pressing public health needs, thus we limited our analysis to the available 2016 data. It is possible that this year of data is not representative of patterns of care in later years, and it limits our ability to assess changes over time or distinguish whether the observed cluster variations reflect a static phenomenon or an evolving trend influenced by selection pressures. However, even this one year of data demonstrates the potential of machine learning methods to evaluate the role of surgical care in distinguishing hospitals in a trauma system. This in turn offers promising insights into optimizing trauma systems and sets a foundation for future research to investigate trends over multiple years of data. CHARS uses discharge data, and there is a potential for coding errors in the data. In addition, not all the recorded diagnosis codes were successfully converted to ISS, which may introduce bias to our ISS calculation. Nevertheless, this bias happened across all TC levels and is less likely to impact the clustering patterns. While conducting this study in different state(s) could provide deeper insights into regional differences and identify overarching latent forces and behaviors, our research is solely focused on Washington State. Nonetheless, our study can serve as a reference for similar analyses in other states, promoting comparative research and broadening our understanding of trauma care dynamics on a larger scale. In terms of the procedures, the HCUP classification tools are not perfect and required manual reclassification. In the absence of standard recoding schemes, however, this improved the accuracy of our analysis. Furthermore, ICD procedure codes do not contain information about the injury's complexity;

again, a standard method of determining this has not been developed. As such, we internally developed PCGs to approximate procedure complexity. In addition, we elected to only include major procedures, to limit the number of variables in the analysis to those that likely require a higher level of expertise. Including the majority of procedures that might reasonably be expected to be available at most hospitals of any TC designation level would not distinguish well between the clusters. Looking at minor procedures, especially with a population that includes patients treated and discharged from the emergency room is a future direction of this work. Finally, this data set only included inpatient information. However, as we were focused on surgical care, this data set captured the relevant patient population. Integrating data from multiple sources, including the emergency departments, prehospital information, and inter-facility transfer information, is now needed to see if this can identify additional distinguishing features. Finally, these results reflect a single trauma system, and evaluation of other trauma systems using similar methods is also needed to validate for generalizability.

3.5 Conclusions

This study analyzed the relationship between the real-life variability in trauma surgical care and state TC designation levels for hospitals in WA using three sets of clustering analyses. By demonstrating that operative trauma and non-trauma care are only partially aligned with the current TC designation level, this study shows that when considering trauma system improvements, not all hospitals with the same TC designation are equivalent in the actual care they provide. This study suggests unsupervised machine learning could be a promising method to offer insight into the contribution of different hospitals in a specific trauma system, helping to identify which hospitals are the optimal candidates for designation level change or the incorporation of additional services. This is crucial if tools to improve trauma systems are going to be developed that can consider a broader and more nuanced range of interventions that goes beyond simply changing the number and/or location of TCs.

Chapter 4

OPTIMIZATION OF STATEWIDE TRAUMA SYSTEMS DRIVEN BY CARE DELIVERY QUALITY AND POPULATION EQUITY

4.1 Introduction

Organized trauma systems are essential in reducing mortality rates [113] among severely injured patients by facilitating timely access to life-saving expertise and interventions. These systems encompass various aspects of care, including pre-hospital services, triage to well-equipped trauma centers, and the timeliness and quality of care provided in such centers. An optimal trauma system seeks to strike a balance between providing access to critical care while avoiding unnecessary duplication of resources that can increase healthcare costs and dilute trauma centers' experience with severe injuries, leading to worse outcomes [114].

The complex interplay between multiple patient and system factors within trauma systems [115–117] has made it challenging to develop standard metrics or methods for assessing access to trauma care. While over 1500 unique metrics have been used to evaluate different aspects of the trauma system [118–121], access to care is typically measured based on geospatial proximity to either a trauma center or emergency medical services. Measuring access to care in trauma systems should involve not only geospatial but also non-geospatial dimensions [122]. Non-geospatial dimensions, such as the quality of care and specific service capacity within the closest healthcare facilities, may exert a more significant influence on patient survival and recovery after injury than geospatial access [123, 124]. However, assessing multiple metrics for trauma care can be challenging because data is often dispersed across different datasets that collect information on different phases of injury care, such as pre-hospital, transport, and in-hospital care.

Despite the significant benefits of trauma systems in reducing mortality rates among severely injured patients, these benefits are not equally shared among all populations in the United States. Disparities in health have been extensively documented in the United States for decades and unfortunately continue to persist despite evidence and calls for their elimination [125]. Disparities in both outcomes and access to definitive trauma care have been identified based on studies of specific injury patterns and sociodemographic groups [126–131]. Various sociodemographic factors, such as race, ethnicity, sex, age (older adults, children), insurance status, and social vulnerability, have been associated with inequities in trauma care or less geospatial access to trauma care [126–131]. To date, a systematic comparison of multiple metrics of access to trauma care for different sociodemographic groups has not been conducted, highlighting the need for more research in this area to ensure equitable access to high-quality trauma care for all populations.

In this study, we developed a framework that includes an optimization model to improve trauma care delivery in Pennsylvania (PA). Our approach guides resource allocation and hospital functioning while maintaining the current number, locations, and levels of existing hospitals. We achieved a practical performance-level allocation that prioritized both quality and equity enhancements, incorporating a combination of geospatial and non-geospatial factors.

4.2 Literature Review

The optimization of trauma systems, including emergency medical services (EMS) and trauma centers, has gained significant attention in recent years. This literature review includes recent studies that focus on different aspects of trauma system optimization.

Optimizing EMS is a crucial component of trauma system optimization. Asgharizadeh et al. (2022) [132] investigated the allocation of emergency stations and determined the optimal number of ambulances for each station. Their objective was to maximize the coverage of emergency demands while minimizing costs. Majzoubi et al. (2012) [133] proposed integer linear and nonlinear programming models for optimizing the deployment and movement of EMS vehicles, ensuring timely and effective response to emergencies. Boutilier et al. (2020) [134] focused on the optimization of the emergency response vehicle location and routing, with a particular emphasis on low- and middle-income countries. By considering uncertainty in travel times and spatial demand characteristics and leveraging robust optimization approaches, they aimed to minimize travel time and improve the efficiency of EMS in trauma systems.

Trauma center optimization is another crucial aspect of improving trauma care within healthcare systems. Hatami et al. (2022) [135] conducted research on identifying the optimal locations for emergency medical centers and allocating ambulances to these selected centers using simulation. Their objective was to maximize the survival rate of patients while minimizing the total cost of the EMS system. Hirpara et al. (2022) [136] focused on determining the optimal number and placement of trauma centers. Using a heuristic approach based on the Particle Swarm Optimization framework, they found the optimal configuration of trauma centers that would minimize mis-triages and ensure timely access to appropriate care. Cho et al. (2014) [137] found the optimal locations for trauma centers and helicopters to maximize the effective coverage of trauma care. They introduced an integrated method to tackle the challenge of nonconvex bilinear terms in the objective function, considering the interplay between trauma centers and helicopters in the overall trauma system. Jansen et al. (2014) [138] focused on geospatially optimizing trauma system configurations, with a specific emphasis on minimizing travel time and system-related undertriage. Given the conflicting objectives involved in trauma system optimization, they employed metaheuristic optimization algorithms within their model to find solutions that balance multiple factors and minimize system inefficiencies.

These studies demonstrate the significance of EMS optimization and trauma center optimization within the broader context of trauma system optimization. Overall, the increasing number of studies in recent years addressing trauma system optimization underscores its significance as an active and evolving area of research. These studies demonstrate the growing interest in improving trauma care delivery through the optimization of resource allocation, patient outcomes, and operational efficiency within trauma systems. Our study aims to optimize the trauma system at a performance level by combining both pre-hospital and in-hospital metrics to improve trauma care quality across EMS and trauma centers. Our focus is on guiding resource allocation to improve care quality and address equity through a systematic framework that includes an optimization model. By integrating these approaches, we aim to achieve an optimized trauma system that enhances patient outcomes and ensures equitable access to quality care.

4.3 Methods

4.3.1 Overview

We developed a systematic framework (Figure 4.1) to optimize statewide trauma systems based on care delivery quality and population equity.

We first established population groups and trauma care quality metrics using routinely collected state data. To create these groups, we considered all possible combinations of categories from sociodemographic factors commonly linked to inequities, such as race, ethnicity, sex, age, insurance status, and social vulnerability. We also included the injury severity score (ISS) as a key factor influencing trauma care quality. We then developed a set of geospatial and non-geospatial metrics informed by extensive literature, expert opinion, and guidelines for early and definitive trauma care components associated with improved outcomes [139–177]. These metrics reflect the quality of trauma care received by injured patients. We used these metrics to analyze and understand variations in access to high-quality trauma care across different sociodemographic groups.

Then, we integrated the metrics into a unified measurement to offer a comprehensive assessment of trauma care quality across all metrics. This approach allows us to identify patterns and trends in the data across hospital and population groups that might be obscured when analyzing each metric separately. To accomplish this, we created a trauma care quality index by weighting the metrics based on their ability to explain overall disparities in access

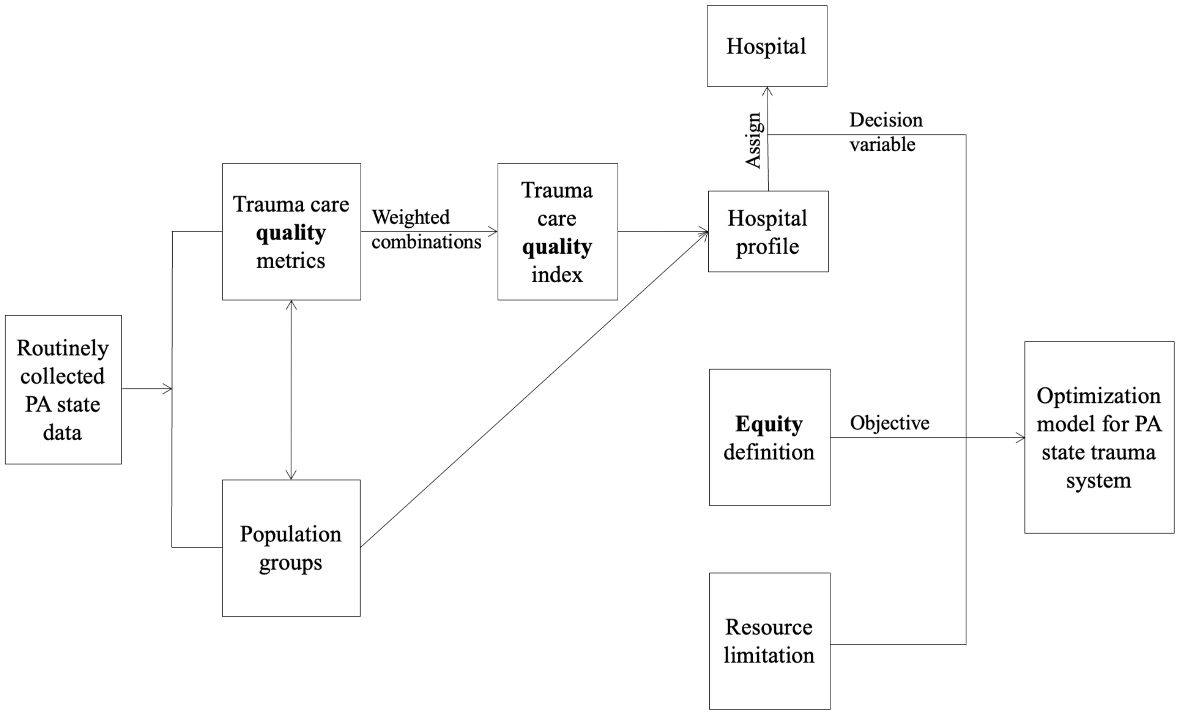


Figure 4.1: Systematic framework for method

to trauma care across hospitals. We determined these weights by performing Principal Component Analysis (PCA) on the metrics. We calculated the quality index for each patient.

Next, we developed a hospital profile for each existing facility using the average trauma care quality index for all sociodemographic groups derived from the data. To address missing data for specific population groups at each hospital, we applied a linear mixed-effects model (LMM) to estimate their quality index. These profiles provide a detailed characterization of the quality of care delivered by each hospital and assess their performance across various population groups. This approach helps identify how well each hospital meets the needs of diverse patient populations and offers insights into their strengths and areas for improvement in trauma care.

Further, we explored several definitions of equity to promote fairness and justice in improving trauma care delivery across different population groups. In the first approach, we assigned greater weight to larger population groups, ensuring that improvements in trauma care benefit a broader segment of the population. In the second approach, we prioritized the most vulnerable groups, focusing on maximizing care quality for those who have historically faced significant barriers to accessing high-quality trauma care. By employing these strategies, we aim to enhance outcomes not only for the overall population but also for those who have been most disadvantaged.

Finally, we developed optimization models with various objective functions to assign hospital profiles to the current hospitals to address equity and improve care quality. We reformulated the non-linear models into mixed-integer linear programming (MILP) problems. The optimal profile generated by the model establishes performance goals for each hospital, and discrepancies between the optimal and current profiles can highlight areas of inefficient or inequitable healthcare resource utilization. By identifying the specific medical resources needed, such as beds and staffing, for each metric that requires improvement, our optimization model provides insights into more effective resource allocation and enhances hospital functioning. This approach aims to enhance both the quality and equity of trauma care delivery across the statewide system.

4.3.2 Data description

We utilized the Pennsylvania Trauma Outcome Study (PTOS) registry data [178]. The PTOS registry, maintained by the Pennsylvania Trauma Systems Foundation, collects comprehensive data on trauma incidents across the state. This dataset includes detailed information on patient demographics, injury characteristics, pre-hospital care, hospital treatment, and outcomes. Key variables in the PTOS registry encompass patient age, sex, race, ethnicity, insurance status, ISS, type and mechanism of injury, pre-existing conditions, transport details, interventions performed, and discharge status. Specifically, we used PTOS data from 2017 to 2020, covering 121,704 patients with 1,476 variables across 43 hospitals in Pennsylvania. This rich dataset allows for an in-depth analysis of trauma care quality and outcomes, providing valuable insights for improving patient care and addressing disparities across different sociodemographic groups. Note that our dataset provides only the unique facility ID and trauma level for each hospital, without additional information to specifically identify each hospital. This represents a limitation of the dataset.

In Pennsylvania, trauma centers are categorized into trauma levels I, II, III, and IV. Research indicates that level I and level II hospitals are major centers of trauma care. These hospitals handle a high volume of complex cases, participate in research, and engage in community outreach, serving as critical components of the trauma system [82]. In contrast, level III and level IV hospitals provide effective care for less severe injuries and are equipped to stabilize critically injured patients before transferring them to higher-level facilities if needed [83].

For this study, we focused exclusively on level I and level II trauma centers, excluding pediatric hospitals. This approach enhances the comparability of trauma care assessments by ensuring that all evaluated hospitals operate under similar resource constraints and capabilities. By concentrating on these levels of trauma centers, we account for variations in hospital resources and expertise, ensuring that the comparison remains fair and relevant. Level I and II non-pediatric hospitals typically have advanced facilities and specialized staff, which standardizes their capacity to manage complex trauma cases. This targeted approach helps ensure that the hospitals are evaluated within a context where they are expected to exhibit similar performance levels, thus providing a more accurate and equitable assessment of trauma care quality. As a result, our analysis includes data from 30 hospitals (70%), offering a comprehensive evaluation of trauma care quality across comparable institutions.

4.3.3 Defining population group based on sociodemographic factors and injury severity

We focused on sociodemographic factors that have been linked to disparities in trauma care or limited geographic access to care. These factors include race, ethnicity, sex, age, insurance type, and Social Deprivation Index (SDI) scores of the residence zip code, which reflect the impact of social indices on care delivery and health outcomes. We combined race and ethnicity categories, as they are correlated, and most patients (92%) are identified as non-Hispanic/Latino. We also included ISS as an important factor. There are multiple categories for each factor, as shown in Table 4.1.

Table 4.1: Sociodemographic factors

Factor	Category
Race and Ethnicity	Hispanic or Latino; Non-Hispanic/Latino White; Non-Hispanic/Latino Black; Non-Hispanic/Latino Asian; Non-Hispanic/Latino Other
Sex	Female; Male
Age*	Children; Younger adults; Older adults
Insurance	Medicare; Medicaid; Commercial; Self-pay; Other
Residence SDI†	Low; Mild; Moderate; High
ISS‡	Severe; Non-severe

*Children with age < 18; younger adults with age ≥ 18 and ≤ 65; older adults with age > 65.

†SDI: Social Deprivation Index. SDI categories are defined by the cut-offs on the SDI scores with the 25%, 50%, and 75% quantiles.

‡ISS: Injury Severity Score. Severe injured with ISS > 15.

Population groups are defined as all the potential combinations of categories within each sociodemographic and injury severity factor in Table 4.1. An example of a population group could be a non-severe injured non-Hispanic/Latino Asian female younger adult with commercial insurance who resides in an area with high SDI. In this study, we considered all existing combinations of population groups across the hospitals included, resulting in a total of 981 distinct population groups. We included patients from level I and II non-pediatric hospitals with no missing in the population factors, resulting in a total of 103,362 (85%) patients.

We did not set a threshold for population size, which may limit the statistical power for groups with smaller populations. Nevertheless, given the availability of several years of data, we believe this approach is valid as it encompasses all existing population groups and captures meaningful variations within the data. Future studies could incorporate a threshold to further refine the analysis.

4.3.4 Trauma care quality metric

We derived 128 metrics related to access to early and definitive trauma care based on the literature [139–177] and expert opinion. These metrics are categorized by the type of care, including timeliness, appropriateness, availability, resource, performance, and outcomes. They covered various phases of care, including prehospital, transport, and in-hospital settings, such as the emergency room, operating room, intensive care unit (ICU), and ward. Detailed lists of the original metrics and the number of relevant patients can be found in Table C.1 and Table C.2. We linked each metric to the corresponding variables in the PTOS dataset and calculated the metric values for each patient based on the data.

This extensive work underscores the significant effort invested in deriving, categorizing, and calculating the metrics, offering valuable insights into the quality of trauma care and identifying areas for improvement. The thorough and detailed process ensured a comprehensive assessment of trauma care quality across different stages and types of care. Importantly, these metrics cover a broad spectrum of factors, not just outcomes like mortality, enabling a more complete evaluation of trauma care delivery, highlighting the thoroughness and depth of our study.

4.3.5 Quality index

We generated a trauma care quality index based on the metrics listed in Section 4.3.4. One simple approach to constructing a composite index for trauma access is by using the geometric mean of the original metrics [179]. Suppose we have n original metrics, the geometric mean is the nth root of the multiplication of all the metrics. This method has several advantages, such as combining metrics with different distributional assumptions and not requiring standardization [179]. Major health-related indices such as the Human Development Index, Socio-demographic Index, and Sustainable Development Goals Index have used the geometric mean method [180–182]. More advanced multivariate analyses can also be used, such as Principal Component Analysis (PCA), factor analysis, and cluster analysis [183].

In this study, we derived a trauma care quality index as a linear combination of the metrics and used PCA to determine the weights for each metric by identifying sources of variation across hospitals. To ensure consistency in the direction of metrics, where higher values indicate better performance, we applied a negative transformation to low-quality indices, converting them into high-quality indices [184]. We also shifted the minimum value to zero to ensure all values are positive. To capture hospital-level variation, we calculated each metric as the average value for the patients in each hospital. We removed metrics that were missing for all patients in any hospital or had the same value across all hospitals. To standardize each metric value and account for differences in units among the trauma care quality metrics, we used min-max standardization [185]. We then performed PCA on the hospitals based on their average scores for the metrics. The quality index was established as a weighted summation of all quality metrics, with the weights obtained from the PCA [103] results, reflecting how well each metric captures the variation among hospitals. This method allows us to create a robust and comprehensive measure of trauma care quality across different institutions.

PCA is an orthogonal linear transformation that projects data to a new coordinate system in which the greatest variance by some scalar projection of the data lies on the first coordinate (first principal component (PC)), the second greatest variance on the second coordinate, and so on [186]. This process removes collinearity among variables and highlights where the most variance occurs across hospitals. To calculate the quality index, we selected the top principal components that together account for 70% of the total variance. We then weighted each PC score by the proportion of variance it captures relative to the total variance captured by the selected PCs and summed these weighted scores [187–190]. Since each PC score is a linear combination of the original metrics, we transformed the PC scores back into their respective linear combinations (loading) of the original metrics. This allowed us to derive weights for each metric, emphasizing those with the most significant disparities across hospitals. This method ensures that metrics with greater variance across hospitals are given more weight in the overall quality index.

Assume we have M metrics with scores $\phi_1, \phi_2, ..., \phi_M$, and we select the top D PCs with scores $z_1, z_2, ..., z_D$ from PCA, which account for variances $v_1, v_2, ..., v_D$. Let β_{md} represent the loading of metric m on PC d $(m = 1, ..., M; d = 1, ..., D)$. The quality index is then calculated as:

$$\Pi = \sum_{d=1}^{D} \frac{v_d z_d}{\sum_{i=1}^{D} v_i} = \sum_{d=1}^{D} \frac{v_d}{\sum_{i=1}^{D} v_i} (\sum_{j=1}^{M} \beta_{jd}\phi_j) = \sum_{j=1}^{M} (\sum_{d=1}^{D} \frac{v_d}{\sum_{i=1}^{D} v_i} \beta_{jd})\phi_j \triangleq \sum_{j=1}^{M} \alpha_j \phi_j \tag{4.1}$$

To calculate the individual quality index for each patient, we first standardized each metric using the min-max standardization method. Since some metrics are not applicable to certain patients, there may be missing data for specific metrics at the patient level. To handle potential missing metrics, we adjusted the weights of the available metrics by re-scaling them based solely on the metrics present for each patient [191]. This approach ensures that the quality index accurately reflects the data available for each individual, providing a fair assessment despite any missing information. Assume $\phi_j, j \in A$ is the set of available metrics for a certain patient, then the quality index for that patient with re-scaling is calculated as:

$$\Pi' = \frac{\sum_{j \in A} \alpha_j \phi_j}{\sum_{j \in A} |\alpha_j|} \tag{4.2}$$

We scaled the quality indexes for all patients to a [0, 1] range using min-max standardization.

Our quality index is heavily data-driven, with the metric weights adaptable to changes in data, such as those from different years or states. This flexibility allows the index to adjust to the specific circumstances of each year or location, reflecting their unique needs and variations. However, this approach also means that the index lacks a fixed formulation, which can limit its generalizability across different contexts.

4.3.6 Hospital profile

We created a profile for each hospital to represent the trauma care quality it provides for each population group. These profiles were derived by calculating the average quality index for each population group within each hospital, accurately reflecting the hospital's current performance in trauma care delivery. We included all existing combinations of sociodemographic and injury severity factors across all hospitals.

For hospitals missing data on certain population groups, we imputed the metric values using predictions from a linear mixed-effects model (LMM). This model incorporated six sociodemographic and injury severity factors, race and ethnicity, sex, age, insurance, residence SDI, and ISS, as categorical (Table 4.1) fixed effects and the hospital ID as a random effect, with the quality index as the response variable. This approach ensured a comprehensive and fair representation of trauma care quality for each hospital, even in the presence of missing data.

The model can be expressed as follows:

$$Y_{q_i} = X_{q_i}^T \beta + Z_i^T b_i + \epsilon_{q_i} \tag{4.3}$$

, where Y_{q_i} represents the quality index of patient q in hospital i, β stands for the coefficients on the sociodemographic and injury severity features, b accounts for the hospital variation, and ϵ accounts for the individual variation.

4.3.7 Equity definition

Equity in distributive justice has several competing definitions. Egalitarianism and utilitarianism are two key concepts that represent opposing schools of thought, with the former advocating for equal distribution of resources and the latter promoting the greatest good for the greatest number [192]. The Nash bargaining solution is another approach that seeks to find a compromise between these two perspectives [193]. It proposes a solution that maximizes the product of gains for each individual in a group while ensuring that the outcome is fair and equitable for everyone involved. Priority, proportionality, and parity can correspond to the utilitarian, Nash bargaining, and egalitarian solutions, respectively [194]. The choice of equity definition depends on societal values and the specific context. Also, equity definitions can vary in their formulation, including linear or non-linear with equal or non-equal weights [195].

One well-known non-linear definition of equity is α-fairness [196]. This family of functions includes several definitions of fairness mentioned earlier: $\alpha = 0$ corresponds to a utilitarian objective, $\alpha = 1$ corresponds to a Nash bargaining or proportionally fair objective, and $\alpha \to \infty$ corresponds to an egalitarian or max-min fair objective [197]. Another well-known equity definition is the L-estimator [198–200] or L-risk [198, 201]. This type of objective has gained attention in machine learning recently [198, 201–207].

Equity definition (4.4) with α-fairness can be written as:

$$\begin{aligned} &\text{Maximize} \quad f(x) \\ &f(x) = \begin{cases} \displaystyle\sum_{p=1}^{P} \frac{\Pi_p^{1-\alpha}}{1-\alpha}, & \alpha \neq 1, \\ \displaystyle\sum_{p=1}^{P} \ln(\Pi_p), & \alpha = 1. \end{cases} \end{aligned} \tag{4.4}$$

Note that $\alpha \geq 0$. A higher value of α indicates a more equitable allocation. $\alpha = 0$ represents the efficient objective with equal weight on each population group. On the other hand, $\alpha > 0$ represents the "α-fair" objective, which focuses more on vulnerable population groups. Two notable values of α are $\alpha = 1$ (proportionally fair) and $\alpha \to \infty$ (egalitarian) [197].

We addressed equity as a variant of L-estimator using weighted maximization on the quality index of population groups [208]. Assume we have P population groups, each with a quality index denoted by Π_p, $p = 1, ..., M$. The corresponding objective is formulated as follows:

$$\text{Maximize} \quad \sum_{s=1}^{P} \sigma_s \Pi_{(s)}. \tag{4.5}$$

Here, $\Pi_{(1)} \leq \cdots \leq \Pi_{(P)}$ represent the order statistics of the quality indexes, and $0 \leq \sigma_P \leq \cdots \leq \sigma_1 \leq 1$ is a sequence of non-increasing weights that satisfy $\sum_{p=1}^{P} \sigma_p = 1$. Objective

(4.5) addresses equity by prioritizing improving trauma care quality for the more vulnerable population groups. The σ in (4.5) allow practitioners to interpolate between average-case ($\sigma_p = \frac{1}{P}, \forall p$) and worst-case ($\sigma_1 = 1$) performance [208]. We adjusted the weight σ of the quality index to place more or less emphasis on certain ordered population groups.

Specifically, we focused on two sets of objective functions in this study: Set 1 weighted the population group quality index by population size, and Set 2 weighted by vulnerability. In Set 1, we assigned greater weight to larger populations, ensuring that improvements in trauma care benefit a broader segment of the population. In Set 2, we prioritized the most vulnerable population groups, focusing on maximizing care quality for those who have historically faced significant barriers to accessing high-quality trauma care.

4.3.8 Optimization model

To ensure consistency and clarity, we utilized the symbols i and j to represent hospitals, p to represent population groups, and q_p to represent patients in population group p throughout the following sections. Please refer to Table 4.2 for further details on the notation used.

Table 4.2: Notation of the optimization model

Notation	Explanation
N	Number of hospitals
P	Number of population groups
Q	Number of total patients
Q_p, $p = 1, ..., P$	Number of patients in population group p
ψ_{pi}, $p = 1, ..., P$, $i = 1, ..., N$	Quality index for population group p in hospital i
Π_p, $p = 1, ..., P$	Quality index of population group p

$\Pi_{(s)},\ s=1,...,P$	sth smallest quality index among all population groups
$\sigma_s,\ s=1,...,P$	Weight assigned to the quality index for population group s
$T^{\S}_{q_p i},\ q_p=1,...,Q_p,\ p=1,...,P,\ i=1,...,N$	Indicator of whether patient q_p in population group p went to hospital i or not
$I^{\dagger}_{ij},\ i,j=1,...,N$	Indicator of whether to assign the profile of hospital i to hospital j or not

$^{\S}T_{q_p i}=1$ if patient q_p in population group p went to hospital i, $T_{q_p i}=0$ otherwise.

$^{\dagger}I_{ij}=1$ if assign profile of hospital i to hospital j, $I_{ij}=0$ otherwise.

We developed the models to optimize the delivery of trauma care in PA by allocating resources while maintaining the current number, locations, and levels of existing hospitals. We assigned hospital profiles to each hospital, driven by both quality and equity improvement. Assigning hospital j with the profile of hospital i means recommending hospital j adopt a resource configuration more similar to hospital i. The optimization model proposed can assist policy-makers in determining how to allocate medical resources combined with discovering the resources related to the quality index. Since trauma center levels are determined by available resources [80], and our focus is on level I and level II non-pediatric hospitals with comparable resources, the model permit any hospital profile to be assigned to any other hospitals. This flexibility in profile assignment is within the context of managing resource limitations. The decision variable for the model is I_{ij}, with $i,j=1,...,N$, which allocated hospital profiles to existing hospitals.

The model for Set 1 weighted by population size is formulated as:

$$\underset{I_{ij}}{\text{Maximize}} \quad \sum_{p=1}^{P} \sigma_p \Pi_p \tag{4.6}$$

$$\text{subject to} \quad \Pi_p = \frac{1}{Q_p} \sum_{q_p=1}^{Q_p} \sum_{j=1}^{N} T_{q_p j} \sum_{i=1}^{N} I_{ij} \psi_{pi}, \quad \text{for} \quad p = 1, ..., P, \tag{4.7}$$

$$\sum_{i=1}^{N} I_{ij} = 1, \quad \text{for} \quad j = 1, ..., N, \tag{4.8}$$

$$I_{ij} \in \{0, 1\}, \quad \text{for} \quad i, j = 1, ..., N, \tag{4.9}$$

, where $\sigma_p = Q_p/Q$ denotes the population size proportion.

Constraint (4.7) calculates the quality index for each population group following profile assignment. It determines the quality index based on the relative values of the assigned profiles. Specifically, if a patient from a given population group is treated at hospital j with the assigned profile of hospital i, the updated quality index for that patient is taken from the profile of hospital i. We assume that a patient's choice of hospital was solely based on the hospital's location, and obtained the patient-hospital assignments using data from the existing trauma registry. Note that the sum of the number of patients in each population group, denoted by $\sum_{p=1}^{P} Q_p$, should equal the total number of patients, denoted by Q. Also note that each patient should only be assigned to one hospital, denoted by $\sum_{i=1}^{N} T_{q_p i} = 1$ for $q = 1, ..., Q_p$ and $p = 1, ..., P$. Constraint (4.8) ensures that each hospital can only be assigned one hospital profile.

The model for Set 2 weighted by the vulnerability is formulated as:

$$\begin{aligned}
&\underset{I_{ij}}{\text{Maximize}} && \sum_{s=1}^{P} \sigma_s \Pi_{(s)} && (4.10)\\
&\text{subject to} && \Pi_p = \frac{1}{Q_p} \sum_{q_p=1}^{Q_p} \sum_{j=1}^{N} T_{q_p j} \sum_{i=1}^{N} I_{ij} \psi_{pi}, \quad \text{for} \quad p = 1, ..., P, && (4.11)\\
& && \sum_{i=1}^{N} I_{ij} = 1, \quad \text{for} \quad j = 1, ..., N, && (4.12)\\
& && I_{ij} \in \{0, 1\}, \quad \text{for} \quad i, j = 1, ..., N, && (4.13)
\end{aligned}$$

The weight σ in (4.10) is a pre-defined weight on the ordered quality index for each population group. It satisfies the conditions $0 \leq \sigma_P \leq \cdots \leq \sigma_1 \leq 1$, and $\sum_{s=1}^{P} \sigma_s = 1$, which ensures equity is addressed when maximizing the overall trauma care quality, with a focus on improving care for vulnerable population groups. We can specialize Model (4.10)-(4.13) as a max-min optimization problem by setting $\sigma_1 = 1$ and $\sigma_s = 0$ for $s = 2, ..., P$:

$$\begin{aligned}
&\underset{I_{ij}}{\text{Maximize}} && \min_{p=1,...,P} \Pi_p && (4.14)\\
&\text{subject to} && \Pi_p = \frac{1}{Q_p} \sum_{q_p=1}^{Q_p} \sum_{j=1}^{N} T_{q_p j} \sum_{i=1}^{N} I_{ij} \psi_{pi}, \quad \text{for} \quad p = 1, ..., P, && (4.15)\\
& && \sum_{i=1}^{N} I_{ij} = 1, \quad \text{for} \quad j = 1, ..., N, && (4.16)\\
& && I_{ij} \in \{0, 1\}, \quad \text{for} \quad i, j = 1, ..., N, && (4.17)
\end{aligned}$$

We reformulated the optimization model (4.10)-(4.13) with a linear objective and additional linear constraints:

$$\underset{I_{ij}, u_s, y_p^{(s)}}{\text{Maximize}} \qquad \sum_{s=1}^{P} \sigma_s u_s \tag{4.18}$$

$$\text{subject to} \qquad u_s \leq \Pi_p + M(1 - y_p^{(s)}), \quad \text{for} \quad s, p = 1, ..., P, \tag{4.19}$$

$$\sum_{p=1}^{P} y_p^{(s)} = P - s + 1, \quad \text{for} \quad s = 1, ..., P, \tag{4.20}$$

$$y^{(s)} \in \{0, 1\}^P, \quad \text{for} \quad s = 1, ..., P, \tag{4.21}$$

$$\Pi_p = \frac{1}{Q_p} \sum_{q_p=1}^{Q_p} \sum_{j=1}^{N} T_{q_p j} \sum_{i=1}^{N} I_{ij} \psi_{pi}, \quad \text{for} \quad p = 1, ..., P, \tag{4.22}$$

$$\sum_{i=1}^{N} I_{ij} = 1, \quad \text{for} \quad j = 1, ..., N, \tag{4.23}$$

$$I_{ij} \in \{0, 1\}, \quad \text{for} \quad i, j = 1, ..., N, \tag{4.24}$$

, where M is a sufficiently large number, for example, 1000.

Specifically, the reformulation for optimization model (4.14)-(4.17) can be simplified as:

$$\underset{I_{ij}, z}{\text{Maximize}} \qquad z \tag{4.25}$$

$$\text{subject to} \qquad z \leq \Pi_p \quad \text{for} \quad p = 1, ..., P, \tag{4.26}$$

$$\Pi_p = \frac{1}{Q_p} \sum_{q_p=1}^{Q_p} \sum_{j=1}^{N} T_{q_p j} \sum_{i=1}^{N} I_{ij} \psi_{pi}, \quad \text{for} \quad p = 1, ..., P, \tag{4.27}$$

$$\sum_{i=1}^{N} I_{ij} = 1, \quad \text{for} \quad j = 1, ..., N, \tag{4.28}$$

$$I_{ij} \in \{0, 1\}, \quad \text{for} \quad i, j = 1, ..., N, \tag{4.29}$$

We formed a mixed-integer linear model [209] in equations (4.18)-(4.24). The model was solved using the Gurobi solver in R.

4.4 Results

4.4.1 Quality index results

As detailed in Sections 4.3.2 and 4.3.3, our analysis covered 30 hospitals, 981 population groups, and 103,362 patients. As detailed in Section 4.3.4, we initially derived 128 trauma care delivery quality metrics (as shown in Table C.1 and Table C.2). After accounting for missing data and metrics with identical values across hospitals, 115 metrics (90%) remained. See the individual-level summary for the remaining metrics in Table C.3.

The PCA analysis of hospital-level average metric values revealed that the top 19 components accounted for over 90% of the variation, with the top 10 components alone capturing more than 70% of the variation. We chose to focus on these top 10 components for further analysis. For details on the variance captured by these components, refer to Figure 4.2. Most indices fall between 0.5 and 0.9 and the highest frequency is observed around the 0.7 to 0.8 range. This skew towards higher values indicates overall positive performance in the assessed metrics, while the smaller proportion of indices below 0.4 highlights areas needing targeted improvements.

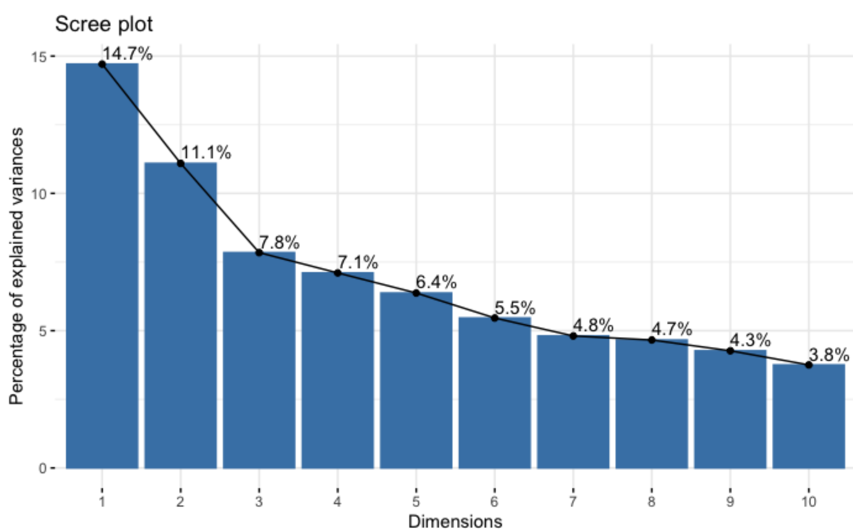


Figure 4.2: Percentage of explained variances of the top 10 principal components

Refer to Fig. 4.3 for the distribution of individual quality indices based on our calculations in Section 4.3.5.

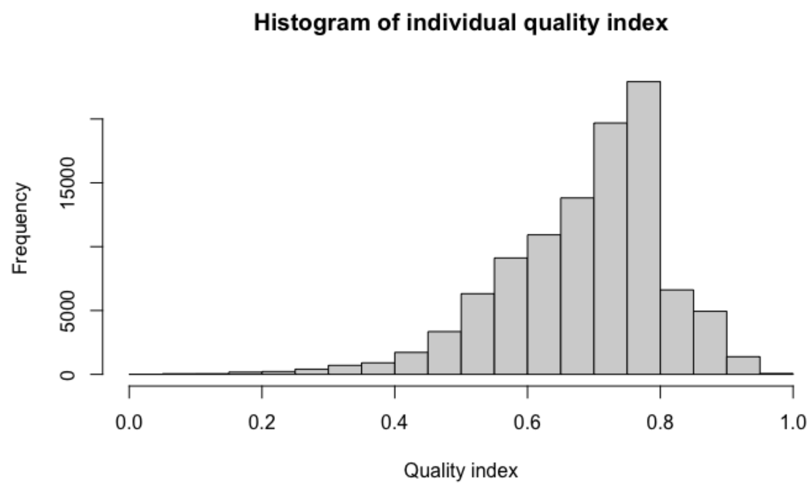


Figure 4.3: Histogram of individual quality index

4.4.2 Hospital profile results

We first constructed the hospital profile using calculated metric scores, which represent the average score across patients in each population group within the hospital. The distribution of the profile quality index from the data is shown in Fig. 4.4.

To impute the missing profile quality indices, we developed an LMM using data from all patients. The results for the random effects and fixed effects of the LMM used for quality index prediction are presented in Table 4.3 and Table 4.4, respectively. Several factors show high significance with p-values less than 0.001, such as sex (male), age (older adults and children), insurance status (Medicare, other, self-pay), and injury severity score (severe). The SDI (moderate) factor is also significant, though to a lesser extent. Other factors, such as race/ethnicity, certain insurance types, and some SDI levels, do not show significant effects.

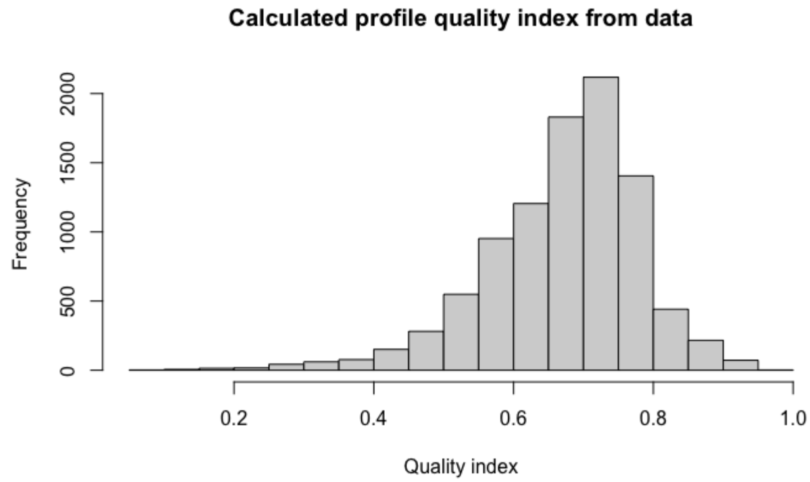


Figure 4.4: Histogram of calculated profile quality index from data

The mean squared error of the model is 0.01 and the mean absolute error is 0.08. The R_m^2 value is 0.1383, indicating that the fixed effects explain approximately 13.83% of the variance. The R_c^2 value is 0.156, showing that the combined fixed and random effects explain approximately 15.60% of the variance in the response variable, quality index. The inclusion of the random effects, hospital variation, increases the explained variance.

Table 4.3: Summary for the random effects of the LMM

Groups	Name	Variance	Std. Dev.
Hospital ID	Intercept	0.0003	0.0162
Residual		0.0125	0.1116

Table 4.4: Summary for the fixed effects of the LMM

Fixed factor	Estimate	Std. Error	df	t value	$\Pr(>\lvert t \rvert)$	Significance§
Intercept	0.7259	0.0045	150	161.73	$< 2 \times 10^{-16}$	***
RaceEthnicity: non-Hispanic/Latino Black	0.0024	0.0034	103300	0.70	0.482	
RaceEthnicity: Hispanic/Latino	0.0030	0.0038	103300	0.80	0.424	
RaceEthnicity: non-Hispanic/Latino Other	-0.0062	0.0044	103300	-1.38	0.167	
RaceEthnicity: non-Hispanic/Latino White	0.0001	0.0032	103300	0.02	0.983	
Sex: male	-0.0065	0.0007	103300	-8.87	$< 2 \times 10^{-16}$	***
Age: older adults	-0.0289	0.0010	103300	-28.36	$< 2 \times 10^{-16}$	***
Age: children	-0.0074	0.0016	103300	-4.75	2.04×10^{-6}	***
Insurance: Medicaid	-0.0013	0.0012	103300	-1.14	0.254	
Insurance: Medicare	-0.0066	0.0012	103300	-5.74	9.40×10^{-9}	***
Insurance: other	0.0136	0.0012	103300	11.35	$< 2 \times 10^{-16}$	***
Insurance: self-pay	-0.0239	0.0020	103300	-11.66	$< 2 \times 10^{-16}$	***
SDI: low	-0.0002	0.0011	102200	-0.17	0.864	
SDI: mild	-0.0009	0.0011	102900	-0.77	0.441	
SDI: moderate	-0.0034	0.0011	103000	-3.08	0.002	**
ISS: severe	-0.1089	0.0009	103300	-119.04	$< 2 \times 10^{-16}$	***

§ The code *** indicates that the factor is highly significant with a p-value less than 0.001.

The code ** indicates that the factor is significant with a p-value between 0.001 and 0.01.
The absence of a symbol indicates a p-value greater than 0.1, suggesting that there is no evidence of the factor being significant.

We imputed the quality index value for missing population groups in each hospital. Refer to Fig. C.1 for the histogram of all the predicted profile quality indices obtained through LMM prediction, and Fig. C.2 for the histogram of indices used as imputed values for the hospital profiles. The histograms reveal two distinct peaks around 0.6 and 0.7. This distribution is consistent with the influence of significant factors, such as the ISS, which notably affects the quality index. Refer to Table 4.5 for the number and proportion of population groups that were absent and imputed for each hospital. The average imputation proportion per hospital is 68%.

Table 4.5: Imputation summary for each hospital

No.	Hospital ID	# Population group imputed	% Population group imputed
1	1	627	64%
2	2	597	61%
3	3	603	61%
4	4	788	80%
5	5	676	69%
6	6	832	85%
7	7	624	64%
8	8	608	62%
9	9	666	68%
10	10	705	72%

11	11	603	61%
12	12	608	62%
13	13	633	65%
14	14	603	61%
15	15	692	71%
16	16	788	80%
17	18	472	48%
18	19	735	75%
19	20	513	52%
20	21	748	76%
21	22	741	76%
22	25	689	70%
23	30	697	71%
24	31	779	79%
25	32	646	66%
26	33	636	65%
27	50	719	73%
28	61	665	68%
29	62	717	73%
30	65	578	59%

By combining the existing quality index from the original dataset with the imputed quality index from the LMM model, the complete distribution used to build the hospital profile is illustrated in Fig. 4.5. The summary in Table 4.6 offers a detailed view of the profile quality index across three sources: calculated from data, LMM-predicted for imputation, and the combined quality index that integrates both sources. The calculated scores show a broader range (0.071 to 0.988) compared to the more narrow range of LMM-predicted scores

(0.516 to 0.771), indicating greater variability in the calculated data. The median values are higher for the calculated and combined data (0.688 and 0.648, respectively) compared to the LMM-predicted scores (0.627), suggesting that the calculated and combined profiles generally reflect higher quality indices. Despite this, the mean values are relatively consistent across all sources (0.671 for calculated, 0.644 for predicted, and 0.651 for combined), demonstrating that the overall average quality index remains stable. This analysis highlights the effectiveness of using both calculated and imputed data to build a comprehensive picture of hospital quality, ensuring a robust and reliable assessment that captures diverse aspects of quality across hospitals.

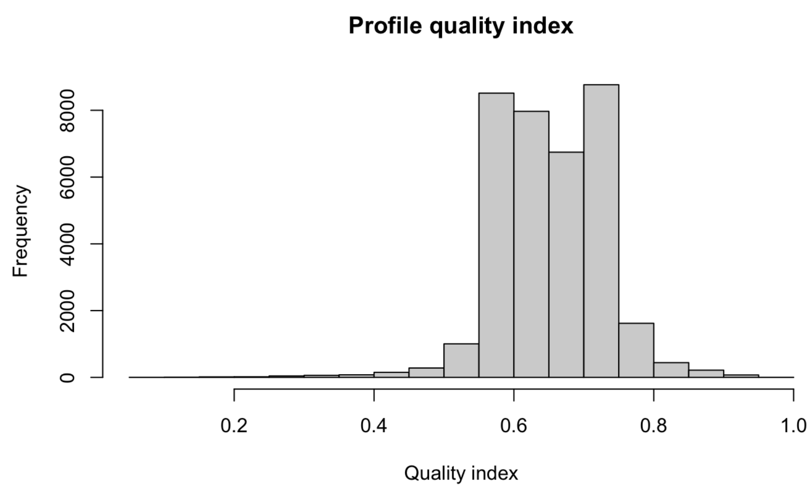


Figure 4.5: Histogram of all profile quality index with imputation

Table 4.6: Summary for the individual quality index

Source	Min	1st quantile	Median	Mean	3rd quantile	Max
Calculated from dataset	0.071	0.609	0.688	0.671	0.744	0.988

Predicted from LMM for imputation	0.516	0.594	0.627	0.644	0.701	0.771
Both sources	0.071	0.595	0.648	0.651	0.709	0.988

4.4.3 Optimization model results

Set 1: weighted by population size

For the first set, we weighted the quality index by population group size. The optimal objective value improved by 4.4%, reaching 0.716 compared to the original value of 0.686 under the current hospital functioning. Refer to Fig. 4.6 for the optimal hospital profile assignment. The model primarily assigns the profile of Hospital 8 to a total of 24 hospitals, including Hospital 8 itself. Additionally, it assigns the profile of Hospital 30 to 5 other hospitals, excluding Hospital 30, and assigns the profile of Hospital 18 specifically to Hospital 33.

The three largest population groups are non-severe injured, non-Hispanic/Latino White older adults with Medicare insurance, living in areas with low, mild, or moderate SDI, followed by three similar groups of non-severe injured, non-Hispanic/Latino White older adult males with Medicare insurance in the same SDI categories. Hospitals assigned the profile of Hospital 8 generally serve the largest populations that align with these major demographic and severity groups. In contrast, the five hospitals assigned the profile of Hospital 30 primarily serve non-severe injured, non-Hispanic/Latino Black younger adult males with Medicaid insurance in high SDI areas, who represent the largest or second-largest proportion at these hospitals. Additionally, these hospitals also commonly serve significant portions of non-severe injured females and severely injured males, both of whom are non-Hispanic/Latino Black younger adults with Medicaid insurance in high SDI areas. This suggests that Hospital 8 excels in trauma care delivery for non-Hispanic/Latino White older adults with Medicare

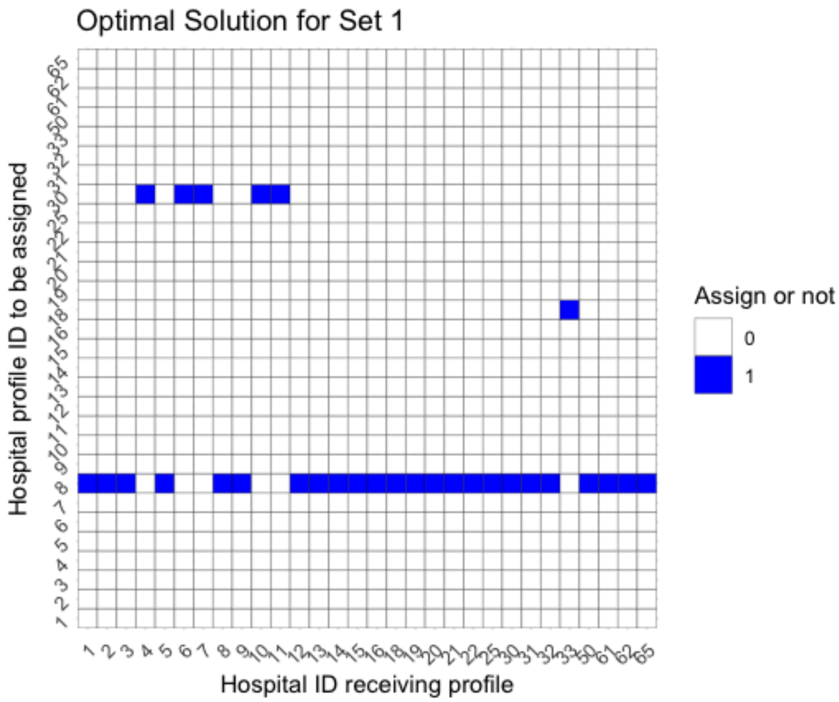


Figure 4.6: Optimal hospital assignment for model Set 1 weighted by population size

insurance, while Hospital 30 may offer superior care for non-Hispanic/Latino Black younger adults with Medicaid insurance in high SDI areas. Additionally, Hospital 8 has the highest average quality index across all population groups, and Hospital 30 ranks second, highlighting their overall high-quality trauma care performance beyond specific demographics.

Hospital 33 being assigned the profile of Hospital 18 instead of 8 or 30 could be due to several factors. It may be due to closer alignment in demographics, care characteristics, and geographic factors. Hospital 33's patient population and care needs may match those of Hospital 18 more closely. Additionally, differences in trauma care quality and resource availability could make Hospital 18's profile a better fit. The optimization model may also have found that assigning Hospital 33 this profile achieves better overall alignment or meets specific criteria more effectively. Specifically, we compared the standardized average scores for each metric across the four hospitals. We calculated the differences between Hospital 18 and the other three hospitals to identify metrics where Hospital 18 performed better and quantified the extent of its superior performance. We found that Hospital 18 outperforms the others, especially in several key metrics: Metric 150 (Retrograde Urethragram (RUG) rates for pelvic fractures), Metric 190 (Massive Transfusion Protocol (MTP) rate for all patients), Metric 190001 (MTP rate for severely injured patients), and Metric 190002 (MTP rate for patients with at least one transfusion). These findings reveal the potential reasons behind the profile assignment for Hospital 33 and highlight areas where it should improve. By using the profile of Hospital 8 as a performance standard, Hospital 33 can better identify specific areas for enhancement and related resource needs to improve its functioning. For RUG rates for pelvic fractures, essential resources can be high-quality imaging equipment, skilled radiologists, and well-established clinical protocols for using RUGs. For MTP rates, hospitals may need an adequate inventory of blood products and efficient transfusion services, including trained staff and emergency preparedness protocols. This involves maintaining a reliable blood bank system, having pre-prepared blood products readily available, and ensuring staff are well-trained in MTP procedures. Effective management and optimization of these resources are crucial for improving performance in the related metrics and enhancing overall trauma care outcomes.

Set 2: weighted by the vulnerability

For the second set, we weighted the quality index by vulnerability, assigning more weight to population groups with poorer quality indices. Instead of considering all 981 population groups, we used two examples: Set 2-1, which assigns a weight of 1 to the worst group, effectively maximizing the minimal performance, and Set 2-2, which distributes equal weights ($\frac{1}{10}$) among the ten worst-performing population groups on the quality index. Note that our optimization model (4.25)-(4.29) offers significant flexibility in weight assignment, allowing for up to 981 non-zero weights to be applied, thereby including all population groups in the objective function.

Set 2-1: maximize the lowest population group quality index

For Set 2-1, maximize the worst population group quality index, the optimal objective value improved by 15.5%, reaching 0.580 compared to the original worst quality index of 0.502 under the current hospital functioning. It shows greater improvement compared to Set 1, implying a focus on overall performance for the current hospital configuration and highlighting the ongoing need to address more vulnerable groups. Refer to Fig. 4.7 for the optimal hospital profile assignment. The model assigns the profile of Hospital 30 to five other hospitals, Hospital 4, 8, and 61 to three others, Hospital 5, 10, 20, and 62 to two others, and Hospital 1, 13, 15, 16, 18, 19, 31, and 32 to one other hospital each. This optimal profile assignment is more varied compared to Set 1, reflecting the shift in focus toward population group equity and highlighting the necessity of the Set 2 vulnerability-weighted analysis. It demonstrates that prioritizing the majority population groups alone can overlook those with the greatest barriers to high-quality trauma care.

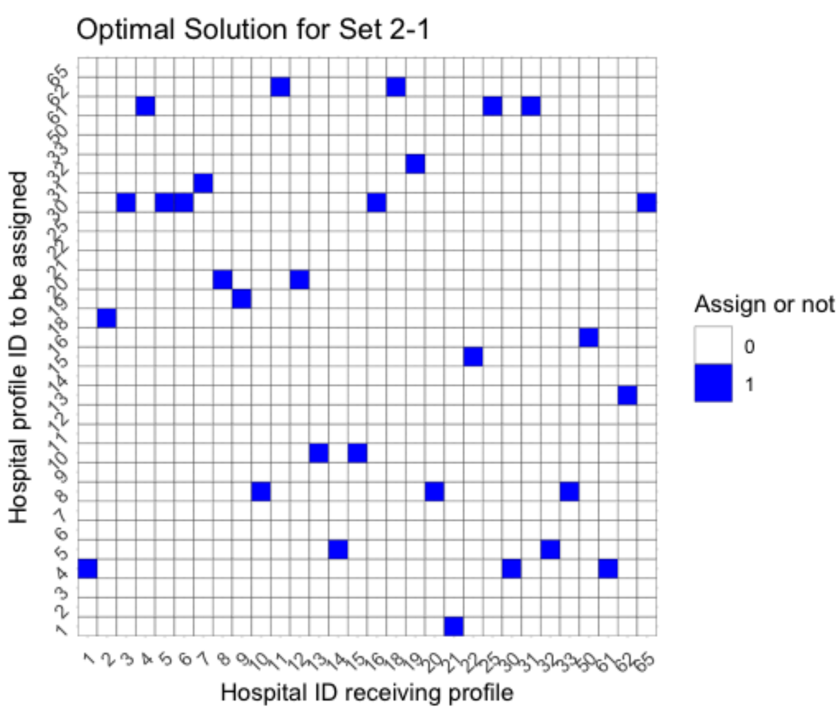


Figure 4.7: Optimal hospital assignment for model Set 2-1 maximize the minimal

Originally, the population group with the worst quality index was severely injured, non-Hispanic/Latino Black younger adult males with self-pay insurance living in high SDI areas. After the optimal hospital profile assignment, the worst quality index now applies to severely injured, non-Hispanic/Latino Other older adults males with self-pay insurance in high SDI areas. Note that given the large number of population groups, many may have similar quality index values. The quality index for the previously worst-performing group improved from 0.580 to 0.585 following the assignment.

For Hospital 30, which was assigned to the most hospitals in this set, we compared its average metric performance with that of the five hospitals it was assigned to: Hospitals 3, 5, 6, 16, and 65. We focused on metrics where Hospital 30's performance exceeded that of the other five hospitals. Key metrics with notable differences include Metric 6 (pre-hospital intubation rate for unconscious patients), Metric 89 (activation rate for patients with respiratory compromise and urgent airway needs), Metric 69 (rate of FAST exams within 15 minutes), and Metric 69001 (rate of FAST exams within 15 minutes for hypotensive patients). These findings suggest that Hospital 30 excels in these areas, indicating that the other five hospitals could benefit from improving their performance related to these specific metrics. Note that the profile of Hospital 30 has also been assigned to other hospitals in Set 1 results, implying that this hospital provides good, though not the best, trauma care delivery quality for both the general population and specific vulnerable groups.

It is notable that Hospital 30's profile was assigned to many other hospitals but not to itself. This suggests the model determined that applying Hospital 30's profile to other facilities would result in significant performance improvements while applying it to Hospital 30 itself might not be as beneficial given its current situation. The model likely found it more optimal to extend Hospital 30's successful practices to other hospitals. When comparing Hospital 30 to Hospital 4, whose profile was assigned to Hospital 30, Hospital 4 notably outperforms Hospital 30 in several metrics, including Metric 11 (rate of airway secured in the ED for patients with GCS < 9), Metric 137 (MRI of spine rate for C-spine injury), Metric 142 (Neck CT rate for C-spine fractures), Metric 143 (Neck CT rate for basilar skull fractures), Metric 227 (Tourniquet rate for penetrating extremity injury), Metric 236 (MRI rate for spine fracture or spinal cord injury), and Metric 272 (Tourniquet rate in place triage). The main resources related to these metrics that Hospital 30 can improve include trained personnel, advanced airway equipment, and rapid response protocols for emergency airway management; access to MRI and CT scanners with trained radiologists for effective diagnostic imaging; and the availability of tourniquet supplies with staff trained in their proper use for trauma care. Addressing these areas involves enhancing the availability and use of diagnostic imaging, improving emergency care practices, and ensuring that the necessary resources and training are in place for effective trauma management. The model suggests Hospital 30 takes the profile of Hospital 4 as a performance standard, with these areas as potential directions to adjust resources and improve hospital functioning.

For all the other hospitals, we could conduct a similar exploration on the profile assignment to identify their assigned performance standards. If a hospital's profile is assigned to other hospitals, we can analyze the metrics to determine the reasons based on hospital comparisons. This process reveals each hospital's strengths and potential areas for improvement, particularly in the context of addressing equity by maximizing the worst population quality index.

Set 2-2: optimize the quality index for the lowest 10 population groups

For Set 2-2, weighted by vulnerability with equal weights for only the worst 10 population group quality index, the optimal objective value improved by 6.8%, reaching 0.581 compared to the original average quality index for the worst 10 population groups of 0.544 under the current hospital functioning. Refer to Fig. 4.8 for the optimal hospital profile assignment. The model assigns the profile of Hospital 30 to seven other hospitals, Hospital 8 to four others, Hospital 19, 20, and 31 to three others, Hospitals 16 and 62 to two others, and Hospital 1, 4, 5, 18, 33, and 61 to one other hospital each. Notably, across Set 1, Set 2-1, and Set 2-2, the profiles of Hospital 30 and Hospital 8 were assigned to a considerable number of hospitals, highlighting their high-quality trauma care for both larger population groups and some of the most vulnerable groups.

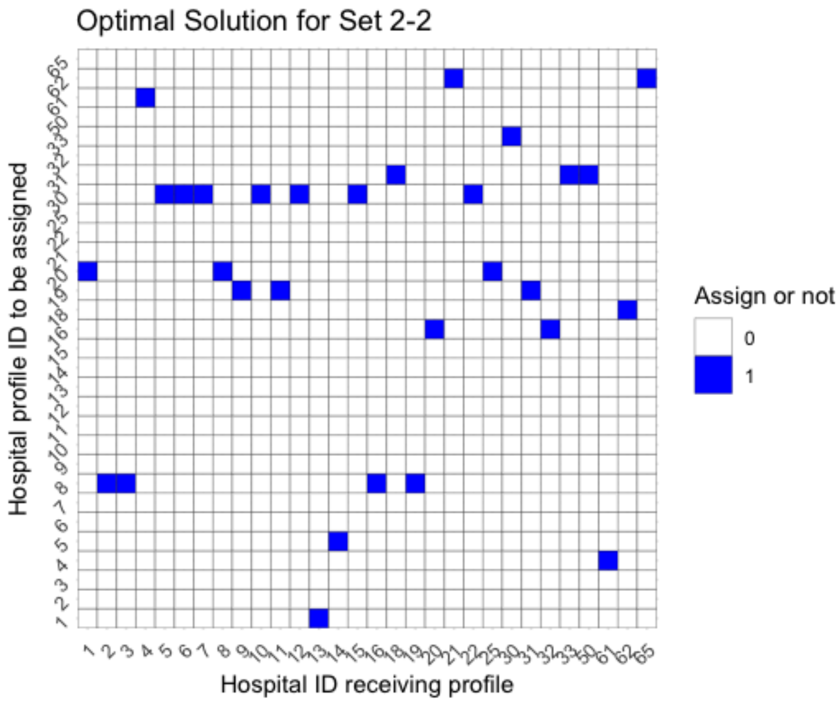


Figure 4.8: Optimal hospital assignment for model Set 2-2 maximize the worst 10

See Table 4.7 for the top 10 worst quality index population groups before assignment and Table 4.8 for the top 10 worst quality index population groups after assignment. Initially, the lowest quality indexes were mostly found among older adults with severe injuries, primarily non-Hispanic/Latino White and Black males with self-pay or Medicare insurance. After the profile assignment, the lowest quality indexes shifted to include more non-Hispanic/Latino Other individuals and older females, with a mix of self-pay and Medicare insurance.

Table 4.7: Population groups with the lowest 10 quality index before profile assignment

No.	Race and Ethnicity	Sex	Age	Insurance	Residence SDI	ISS
1	non-Hispanic/Latino Other	Male	Older adults	Self-pay	High	Severe
2	non-Hispanic/Latino Black	Male	Younger adults	Medicare	High	Severe

3	non-Hispanic/Latino White	Male	Older adults	Self-pay	Low	Severe
4	non-Hispanic/Latino White	Male	Older adults	Medicare	Moderate	Severe
5	Hispanic/Latino	Female	Older adults	Medicare	High	Severe
6	non-Hispanic/Latino White	Male	Younger adults	Self-pay	Low	Severe
7	non-Hispanic/Latino White	Female	Older adults	Self-pay	Mild	Severe
8	non-Hispanic/Latino White	Female	Older adults	Self-pay	Moderate	Severe
9	non-Hispanic/Latino Black	Male	Older adults	Self-pay	Mild	Severe
10	non-Hispanic/Latino Other	Male	Older adults	Medicare	Moderate	Severe

Table 4.8: Population groups with the lowest 10 quality index after profile assignment

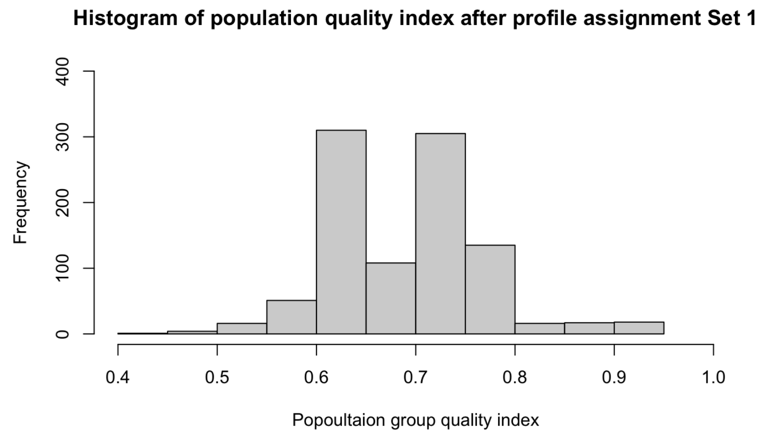
No.	Race and Ethnicity	Sex	Age	Insurance	Residence SDI	ISS
1	Non-Hispanic/Latino Other	Male	Older adults	Self-pay	High	Severe
2	Non-Hispanic/Latino Other	Female	Older adults	Self-pay	High	Severe
3	Non-Hispanic/Latino Black	Male	Older adults	Self-pay	Mild	Severe
4	Non-Hispanic/Latino White	Male	Older adults	Self-pay	High	Severe
5	Non-Hispanic/Latino White	Male	Older adults	Self-pay	Low	Severe
6	Non-Hispanic/Latino Black	Male	Older adults	Self-pay	High	Severe
7	Hispanic/Latino	Male	Older adults	Self-pay	Low	Severe
8	Non-Hispanic/Latino Other	Male	Older adults	Medicare	Low	Severe
9	Non-Hispanic/Latino Black	Male	Older adults	Medicare	Moderate	Severe
10	Non-Hispanic/Latino Black	Female	Older adults	Self-pay	Mild	Severe

For all hospitals, similar analyses as conducted in Set 1 and Set 2-1 can be applied to examine profile assignments and identify their performance standards. By evaluating how a hospital's profile is assigned to other hospitals, we can analyze specific metrics to uncover reasons for these assignments based on hospital comparisons. This approach highlights each hospital's strengths and pinpoints areas for improvement, with a particular focus on addressing equity by maximizing the quality index for the more disadvantaged population groups.

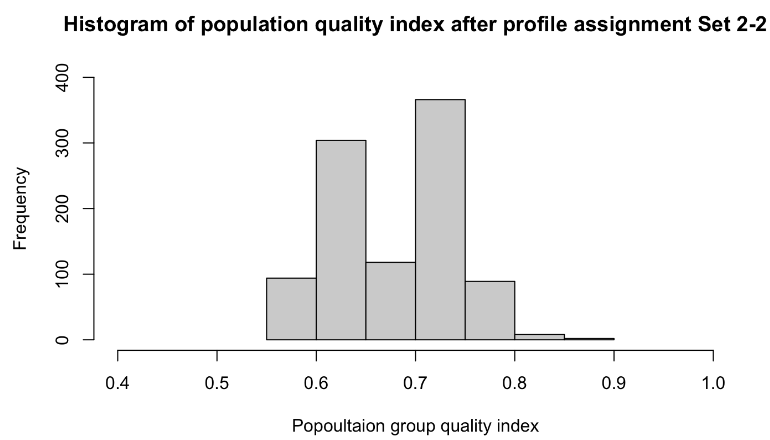
See Fig. 4.9 for the histogram illustrating the Population Group Quality Index under optimal profile assignment for the three sets. The histogram reveals several key insights: when prioritizing larger population groups (Set 1), the highest quality index achieved is greater, indicating better performance for the best-served groups, but the worst quality index is lower, reflecting poorer outcomes for the least-served groups. Conversely, Set 2-2, which prioritizes more vulnerable groups, results in a higher minimum quality index across all population groups, though the maximum quality index is lower, indicating a more balanced distribution of quality that enhances equity but slightly compromises peak performance. Lastly, Set 2-1, focusing solely on the most vulnerable group, leads to the highest minimum quality index, ensuring no group experiences very poor outcomes, but also results in the lowest maximum quality index, indicating a reduction in the best performance achieved. These observations highlight a fundamental trade-off between overall performance and equity: prioritizing larger population groups improves peak performance but can widen disparities, while prioritizing vulnerable groups enhances equity by lifting the lowest-performing groups but may lower peak performance. This trade-off underscores the importance of carefully considering objectives and priorities when designing optimal profile assignments, as strategies favoring overall performance might differ from those aimed at maximizing equity.

4.5 Discussion

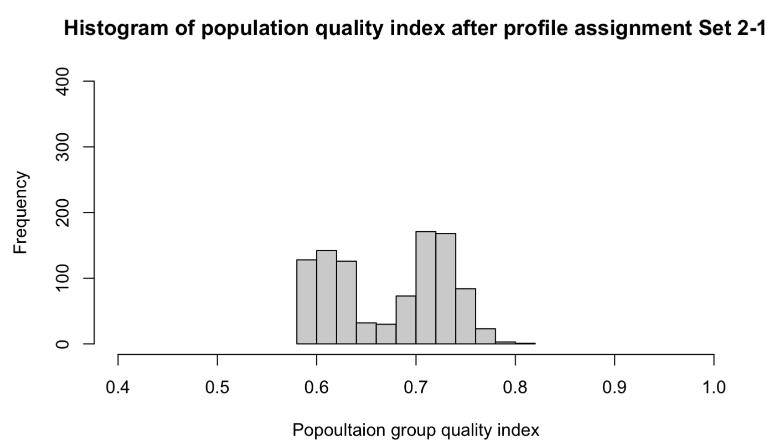
The results from the three optimization sets reveal trade-offs between overall performance and equity in trauma care. Set 1, which weights the quality index by population size, achieved a 4.4% improvement in the objective value, reaching 0.716 from 0.686. This approach prioritizes larger population groups, resulting in a higher peak quality index but a



(a) Population group quality index histogram for Set 1: weighted by population size



(b) Population group quality index histogram for Set 2-2: maximize the worst ten groups



(c) Population group quality index histogram for Set 2-1: maximize the worst group

Figure 4.9: Population group quality index histogram under optimal profile assignment

lower minimum index, reflecting greater disparities among the least-served groups. Hospital 8, assigned to 24 hospitals, delivers high-quality trauma care overall and is likely particularly effective in treating non-severe injuries among non-Hispanic/Latino White older adults with Medicare insurance. Hospital 30, assigned to 5 hospitals, also provides high-quality trauma care and may demonstrate notable strength in serving non-Hispanic/Latino Black younger adults with Medicaid in high SDI areas.

Set 2, which focuses on vulnerability, represents a shift towards equity in trauma care. Set 2-1, aimed at maximizing the lowest quality index, achieved a 15.5% improvement, rising from 0.502 to 0.580. This set features a wider variation in hospital profile assignments compared to Set 1, reflecting a greater emphasis on equity and resulting in the most significant enhancement of the worst quality index across all the optimization sets. Hospital 30's profile, assigned to multiple hospitals, excels in specific metrics such as FAST exams, indicating areas where other hospitals could improve. Meanwhile, Hospital 30's own profile assignment indicates potential areas for improvement, including tourniquet care, MRI and CT imaging, and airway management. Set 2-2, which optimizes the quality index for the ten worst-performing groups, improved by 6.8% to 0.581. This approach results in a higher minimum quality index but a lower maximum index compared to Set 1, leading to a more balanced quality distribution with minor reductions in peak performance.

The results of the optimization models offer each hospital valuable insights into profile assignments and performance standards. By evaluating how a hospital's profile is assigned to other hospitals, the model enables a detailed analysis of specific metrics, uncovering reasons for these assignments based on hospital comparisons. This approach highlights each hospital's strengths and identifies areas for improvement, particularly in addressing equity by maximizing the quality index for the most disadvantaged population groups. It also helps identify related resources necessary for enhancing performance, guiding hospitals in targeted improvements to better serve diverse patient populations.

4.5.1 Contributions

The study has four main contributions. The first contribution is providing a comprehensive analysis of a combination of geospatial and non-geospatial metrics of access to trauma care and identifying disparities in access to care among different sociodemographic groups. Moreover, the development of a quality care index by combining these metrics aids in prioritizing data collection on injuries and determining which metrics are crucial in measuring disparities in high-quality trauma care access.

The second contribution is the study's focus on both trauma care quality and equity. While quality measures are essential for improving the overall patient outcomes in the trauma system, solely focusing on quality may lead to disparities in access and outcomes for different sociodemographic groups. On the other hand, solely focusing on equity may lead to compromised care quality, which could result in worse outcomes for all patients. This study develops an index that takes into account various metrics to assess the quality of trauma care received by injured patients, with a specific focus on equity considerations among different population groups. By using this quality index alongside equity formulations to optimize resource allocation, this study prioritizes both quality and equity enhancements of trauma care delivery in optimizing a trauma system.

The third contribution is the development of a performance-target optimization model for resource allocation that addresses equity and improves care quality in a practical way. The model takes full use of the current configuration for each hospital, which enables decision-makers in the healthcare system to allocate limited resources and reduce medical underuse and overuse [210] accordingly to the optimal performance goals while keeping the existing number, locations, and levels of hospitals intact. By developing this model, this study offers insights into medical resource allocation to improve the quality and equity of trauma care delivery without requiring additional investments in hospital dismantlement, rebuilding, and infrastructure makeover. This approach can help inform policy and decision-making in the healthcare system and ultimately improve patient outcomes.

The fourth contribution is the innovative use of various statistical analyses, machine learning, and optimization methods to evaluate and optimize the delivery of trauma care. By integrating these methods, this study quantified the quality and equity of trauma care delivery and developed optimal hospital functioning adjustment strategies considering the current possible configuration for each hospital under limited resources. The methods employed in this study enable the identification of complex patterns and relationships within the data that would not be apparent using traditional statistical methods alone. Moreover, the flexible use of statistical, machine learning, and optimization techniques demonstrated in this study provides a blueprint for future research in various healthcare applications. This study provides a road map for similar studies that seek to optimize healthcare systems and improve care delivery through a holistic and interdisciplinary approach.

4.5.2 Future directions

Future research could explore several modifications to enhance the optimization model. One promising approach is the integration of additional constraints related to resource limitations. For example, incorporating a cost associated with each profile assignment and setting an upper limit on the total cost could improve the model's ability to maximize the quality index improvement per unit cost. This adjustment is particularly relevant in resource-constrained settings. Additionally, including data on hospital capacity and resource availability, such as bed, staff, and equipment availability, would prevent hospitals from becoming either overburdened or underutilized. This approach would not only enhance the overall quality of care but also ensure that resources are utilized in a way that maximizes their impact.

Another valuable direction is to account for patient choice in the optimization model. Recognizing the importance of patient preferences, the model could incorporate patient-hospital assignments as a decision variable. Allowing patients to choose from a set of eligible hospitals while adhering to care guidelines could create a more flexible and patient-centered healthcare system. This approach might involve considering factors such as transportation time and distance, which significantly affect patient outcomes and resource allocation decisions. By integrating these variables, the model could better address disparities in access to care and ensure equitable access to high-quality healthcare services.

Lastly, incorporating uncertainty into the model could provide a more realistic evaluation of resource allocation strategies. In practice, the quality of care can be influenced by fluctuating factors like staffing levels, patient volume, and resource availability. Introducing stochastic elements into the model, such as random variations in quality metrics or resource availability, and employing stochastic and robust optimization techniques could help assess the robustness of different strategies under varying scenarios. This would allow policymakers to understand how various resource allocation strategies perform under uncertainty and develop more effective policies to improve trauma care delivery.

4.6 Conclusions

This study presents a systematic framework for optimizing statewide trauma systems by integrating both care quality and population equity. Using state data, we established trauma care quality metrics and combined sociodemographic factors and Injury Severity Score (ISS) to create population groups. Using Principal Component Analysis (PCA), we weighted these metrics to account for hospital variation and established a quality index to assess trauma care delivery performance. Hospital profiles were developed and imputed using a linear mixed-effects model, revealing care performance across different population groups.

Our approach applied two key strategies: prioritizing larger population groups and addressing historically disadvantaged groups. The optimization models, reformulated as MILP problems, assigned hospital profiles and highlighted discrepancies between current and optimal profiles. These insights guided effective resource allocation and recommended specific improvements, such as enhancing imaging capabilities and emergency protocols.

A critical finding of this study is the trade-off between overall performance and equity. When focusing on larger population groups, the models achieved higher performance levels but at the expense of greater disparities in care quality for vulnerable populations. Conversely, prioritizing equity led to improvements in care quality for the most disadvantaged groups, although this approach resulted in slightly reduced peak performance.

Ultimately, this framework offers actionable insights for enhancing trauma care systems. It emphasizes the need to balance overall performance with equity considerations to ensure both high standards of care and the needs of diverse populations are met. By guiding hospitals in aligning their performance with optimal profiles and addressing specific areas for improvement, this approach aims to elevate care standards and promote a more equitable trauma care system.

Chapter 5

CONCLUSION

This dissertation advances healthcare effectiveness and equity by offering a comprehensive analysis of remote care technologies, trauma system variability, and hospital performance optimization. By evaluating remote monitoring technologies for chronic conditions such as chronic depression, the research demonstrates how these innovations can enhance personalized care and deliver cost-effective solutions. The findings underscore the potential for remote care to improve patient outcomes while managing healthcare costs. Additionally, by examining variability within trauma systems and identifying gaps in care quality, the dissertation reveals significant disparities that current trauma center designations fail to address. This research highlights the need for hospital-level, data-driven approaches to trauma care management that can improve both effectiveness and equity in acute care settings. By setting optimized performance targets for hospitals, the dissertation ensures that advancements in care are applied in ways that benefit diverse patient populations, ultimately promoting a more equitable healthcare system.

The dissertation also introduces comprehensive methodological frameworks that serve as valuable blueprints for future research, integrating decision-analytic, machine learning, and optimization models based on patient-level data. For example, the decision-analytic model employs a Markov-cohort approach to simulate disease progression and evaluate cost-effectiveness, offering detailed insights into remote monitoring technologies. Machine learning techniques, such as unsupervised clustering, are used to reveal patterns and discrepancies in trauma care that conventional methods might overlook. Additionally, optimization models, including mixed-integer linear programming, are developed to guide resource allocation and improve performance. These multidisciplinary frameworks not only bridge theoretical insights with practical applications but also provide adaptable tools for addressing real-world healthcare challenges. By combining these methodologies, the research delivers actionable insights for enhancing healthcare delivery while establishing a foundation for future studies to further develop and extend these analytical approaches.

This dissertation provides actionable guidelines for enhancing chronic disease management in remote settings and improving the quality and equity of statewide acute trauma care systems. By evaluating remote monitoring technologies, it offers strategic recommendations for their effective implementation, addressing key development factors and various scenarios. These insights suggest that remote care technologies can be integrated into healthcare systems for efficient chronic condition management. Meanwhile, the research's focus on trauma care variability and the development of performance-target optimization models offers valuable strategies for improving acute trauma care delivery. By addressing disparities and leveraging comprehensive metrics, the guidelines support targeted resource allocation strategies that enhance both care quality and equity. Designed to inform policy and practice, these recommendations aim to improve patient outcomes and promote a more equitable distribution of healthcare resources. Overall, the dissertation's contributions present a holistic approach to advancing healthcare delivery, ensuring that innovations and improvements yield meaningful benefits for diverse patient populations in both remote and in-person care settings.

BIBLIOGRAPHY

[1] Gary Fanjiang, Jerome H Grossman, W Dale Compton, and Proctor P Reid. *Building a better delivery system: a new engineering/health care partnership*. National Academies Press, 2005.

[2] Committee on Quality of Health Care in America. *Crossing the quality chasm: a new health system for the 21st century*. National Academies Press, 2001.

[3] Donald M Berwick and Andrew D Hackbarth. Eliminating waste in us health care. *Jama*, 307(14):1513–1516, 2012.

[4] WHO Commission on Social Determinants of Health and World Health Organization. *Closing the gap in a generation: health equity through action on the social determinants of health: Commission on Social Determinants of Health final report*. World Health Organization, 2008.

[5] Paula Braveman. What are health disparities and health equity? we need to be clear. *Public health reports*, 129(1_suppl2):5–8, 2014.

[6] Jonathan Arend, Jenny Tsang-Quinn, Claudia Levine, and David Thomas. The patient-centered medical home: history, components, and review of the evidence. *Mount Sinai Journal of Medicine: A Journal of Translational and Personalized Medicine*, 79(4):433–450, 2012.

[7] Tanya GK Bentley, Rachel M Effros, Kartika Palar, and Emmett B Keeler. Waste in the us health care system: a conceptual framework. *The Milbank Quarterly*, 86(4):629–659, 2008.

[8] Kenneth V Iserson and John C Moskop. Triage in medicine, part i: concept, history, and types. *Annals of emergency medicine*, 49(3):275–281, 2007.

[9] Joseph Kvedar, Molly Joel Coye, and Wendy Everett. Connected health: a review of technologies and strategies to improve patient care with telemedicine and telehealth. *Health affairs*, 33(2):194–199, 2014.

[10] Amy M Bauer, Stephen M Thielke, Wayne Katon, Jürgen Unützer, and Patricia Areán. Aligning health information technologies with effective service delivery models to improve chronic disease care. *Preventive medicine*, 66:167–172, 2014.

[11] Muhammad Imran Razzak, Muhammad Imran, and Guandong Xu. Big data analytics for preventive medicine. *Neural Computing and Applications*, 32(9):4417–4451, 2020.

[12] Cong Peng, Prashant Goswami, and Guohua Bai. A literature review of current technologies on health data integration for patient-centered health management. *Health informatics journal*, 26(3):1926–1951, 2020.

[13] Manmeet Kaur. Application of mixed method approach in public health research. *Indian Journal of Community Medicine*, 41(2):93–97, 2016.

[14] Alvin Rajkomar, Jeffrey Dean, and Isaac Kohane. Machine learning in medicine. *New England Journal of Medicine*, 380(14):1347–1358, 2019.

[15] Uwe Siebert. When should decision-analytic modeling be used in the economic evaluation of health care?, 2003.

[16] Andrew Gelman and Jennifer Hill. *Data analysis using regression and multilevel/hierarchical models*. Cambridge university press, 2007.

[17] Craig W Kirkwood. Strategic decision making multiobjective decision analysis with spreadsheets. *Journal of the Operational Research Society*, 49(1):96–97, 1998.

[18] Magaly Ramirez, Shinyi Wu, Haomiao Jin, Kathleen Ell, Sandra Gross-Schulman, Laura Myerchin Sklaroff, Jeffrey Guterman, et al. Automated remote monitoring of depression: acceptance among low-income patients in diabetes disease management. *JMIR mental health*, 3(1):e4823, 2016.

[19] Marijn Muurling, Casper de Boer, Rouba Kozak, Dorota Religa, Ivan Koychev, Herman Verheij, Vera JM Nies, Alexander Duyndam, Meemansa Sood, Holger Fröhlich, et al. Remote monitoring technologies in alzheimer's disease: design of the radar-ad study. *Alzheimer's research & therapy*, 13(1):1–13, 2021.

[20] Sebastian Hermes, Tobias Riasanow, Eric K Clemons, Markus Böhm, and Helmut Krcmar. The digital transformation of the healthcare industry: exploring the rise of emerging platform ecosystems and their influence on the role of patients. *Business Research*, 13:1033–1069, 2020.

[21] Centers for Disease Control and Prevention. Mental Health Conditions: Depression and Anxiety. https://www.cdc.gov/tobacco/campaign/tips/diseases/depression-anxiety.html. [Online; accessed 15-May-2023].

[22] US Department of Health, Human Services, et al. Major depression. national institute of mental health, 2022.

[23] Robert F Dickerson, Eugenia I Gorlin, and John A Stankovic. Empath: a continuous remote emotional health monitoring system for depressive illness. In *Proceedings of the 2nd Conference on Wireless Health*, pages 1–10, 2011.

[24] American Psychological Association. Clinical Practice Guideline for the Treatment of Depression Across Three Age Cohorts. https://www.apa.org/depression-guideline. [Online; accessed 15-May-2023].

[25] Institute for Clinical Systems Improvement. Depression, Adult in Primary Care. https://www.icsi.org/guideline/depression/. [Online; accessed 15-May-2023].

[26] Department of Veterans Affairs and Department of Defense. VA/DoD Major Depressive Disorder Clinical Practice Guideline. https://www.healthquality.va.gov/guidelines/MH/mdd/VADoDMDDCPGFINAL82916.pdf. [Online; accessed 15-May-2023].

[27] Kaiser Permanente. Adult & Adolescent Depression Screening, Diagnosis, and Treatment Guideline. https://wa.kaiserpermanente.org/static/pdf/public/guidelines/depression.pdf. [Online; accessed 15-May-2023].

[28] Software Advice. Remote Patient Monitoring. https://www.softwareadvice.com/remote-patient-monitoring/remote-patient-monitoring-software-profile/. [Online; accessed 15-May-2023].

[29] Software Advice. RPMPRO. https://www.softwareadvice.com/remote-patient-monitoring/rpmpro-profile/. [Online; accessed 15-May-2023].

[30] Cara C Lewis, Meredith Boyd, Ajeng Puspitasari, Elena Navarro, Jacqueline Howard, Hannah Kassab, Mira Hoffman, Kelli Scott, Aaron Lyon, Susan Douglas, et al. Implementing measurement-based care in behavioral health: a review. *JAMA psychiatry*, 76(3):324–335, 2019.

[31] Tong Guo, Yu-Tao Xiang, LE Xiao, Chang-Qing Hu, Helen FK Chiu, Gabor S Ungvari, Christoph U Correll, Kelly YC Lai, Lei Feng, Ying Geng, et al. Measurement-based care versus standard care for major depression: a randomized controlled trial with blind raters. *American Journal of Psychiatry*, 172(10):1004–1013, 2015.

[32] Michael F Drummond, Mark J Sculpher, Karl Claxton, Greg L Stoddart, and George W Torrance. *Methods for the economic evaluation of health care programmes.* Oxford university press, 2015.

[33] Ray Robinson. Cost-effectiveness analysis. *British Medical Journal*, 307(6907):793–795, 1993.

[34] Christopher McCabe, Karl Claxton, and Anthony J Culyer. The nice cost-effectiveness threshold: what it is and what that means. *Pharmacoeconomics*, 26:733–744, 2008.

[35] Christian Brettschneider, Sebastian Kohlmann, Benjamin Gierk, Bernd Löwe, and Hans-Helmut König. Depression screening with patient-targeted feedback in cardiology: The cost-effectiveness of depscreen-info. *PLoS One*, 12(8):e0181021, 2017.

[36] Mike Paulden, Stephen Palmer, Catherine Hewitt, and Simon Gilbody. Screening for postnatal depression in primary care: cost effectiveness analysis. *Bmj*, 339, 2009.

[37] Gregory E Simon, Wayne J Katon, Elizabeth HB Lin, Carolyn Rutter, Willard G Manning, Michael Von Korff, Paul Ciechanowski, Evette J Ludman, and Bessie A Young. Cost-effectiveness of systematic depression treatment among people with diabetes mellitus. *Archives of general psychiatry*, 64(1):65–72, 2007.

[38] Elbert S Huang, Michael O'Grady, Anirban Basu, Aaron Winn, Priya John, Joyce Lee, David Meltzer, Craig Kollman, Lori Laffel, William Tamborlane, et al. The cost-effectiveness of continuous glucose monitoring in type 1 diabetes. *Diabetes Care*, 33(6):1269–1274, 2010.

[39] S Pinar Bilir, Richard Hellmund, Beth Wehler, Huimin Li, Julie Munakata, and Mark Lamotte. Cost-effectiveness analysis of a flash glucose monitoring system for patients with type 1 diabetes receiving intensive insulin treatment in sweden. *European endocrinology*, 14(2):73, 2018.

[40] Eran Bendavid, Sean D Young, David A Katzenstein, Ahmed M Bayoumi, Gillian D Sanders, and Douglas K Owens. Cost-effectiveness of hiv monitoring strategies in resource-limited settings: a southern african analysis. *Archives of internal medicine*, 168(17):1910–1918, 2008.

[41] Elizabeth A Brooks and Marc Massanari. Cost-effectiveness analysis of monitoring fractional exhaled nitric oxide (feno) in the management of asthma. *Managed Care (Langhorne, Pa.)*, 27(7):42–48, 2018.

[42] Hao-Min Cheng, Alan Pearson, Shih-Hsien Sung, Wen-Chung Yu, Chen-Huan Chen, and Jonathan Karnon. Cost-effectiveness of noninvasive central blood pressure monitoring in the diagnosis of hypertension. *American journal of hypertension*, 28(5):604–614, 2015.

[43] David B Lindenmayer and Gene E Likens. Adaptive monitoring: a new paradigm for long-term research and monitoring. *Trends in ecology & evolution*, 24(9):482–486, 2009.

[44] Ying Lin, Shuai Huang, Gregory E Simon, and Shan Liu. Cost-effectiveness analysis of prognostic-based depression monitoring. *IISE Transactions on Healthcare Systems Engineering*, 9(1):41–54, 2019.

[45] Kurt Kroenke. PHQ-9 (Patient Health Questionnaire-9). https://www.mdcalc.com/calc/1725/phq9-patient-health-questionnaire9. [Online; accessed 15-May-2023].

[46] Kurt Kroenke, Robert L Spitzer, and Janet BW Williams. The phq-9: validity of a brief depression severity measure. *Journal of general internal medicine*, 16(9):606–613, 2001.

[47] SW Roberts. Control chart tests based on geometric moving averages. *Technometrics*, 42(1):97–101, 2000.

[48] Stuart Lloyd. Least squares quantization in pcm. *IEEE transactions on information theory*, 28(2):129–137, 1982.

[49] Wikipedia. Euclidean distance. https://en.wikipedia.org/wiki/Euclidean_distance. [Online; accessed 15-May-2023].

[50] Xuelu Yang. Cost-effectiveness analysis of adaptive monitoring strategies for depression treatment. Master's thesis, University of Washington, 2016.

[51] Eric L Ross, Sandeep Vijan, Erin M Miller, Marcia Valenstein, and Kara Zivin. The cost-effectiveness of cognitive behavioral therapy versus second-generation antidepressants for initial treatment of major depressive disorder in the united states: a decision analytic model. *Annals of internal medicine*, 171(11):785–795, 2019.

[52] Armin Szegedi, Wim T Jansen, Aden PP van Willigenburg, Eghert van der Meulen, Hans H Stassen, Michael E Thase, et al. Early improvement in the first 2 weeks as a predictor of treatment outcome in patients with major depressive disorder: a meta-analysis including 6562 patients. *Journal of Clinical Psychiatry*, 70(3):344, 2009.

[53] National Institute for Health and Care Excellence. Depression in children and young people: identification and management. https://www.nice.org.uk/guidance/ng134. [Online; accessed 15-May-2023].

[54] Gillian D Sanders, Peter J Neumann, Anirban Basu, Dan W Brock, David Feeny, Murray Krahn, Karen M Kuntz, David O Meltzer, Douglas K Owens, Lisa A Prosser, et al. Recommendations for conduct, methodological practices, and reporting of cost-effectiveness analyses: second panel on cost-effectiveness in health and medicine. *Jama*, 316(10):1093–1103, 2016.

[55] Centers for Disease Control and Prevention. Life Tables. https://www.cdc.gov/nchs/products/life_tables.htm. [Online; accessed 16-May-2023].

[56] Pim Cuijpers, Nicole Vogelzangs, Jos Twisk, Annet Kleiboer, Juan Li, and Brenda W Penninx. Comprehensive meta-analysis of excess mortality in depression in the general community versus patients with specific illnesses. *American journal of psychiatry*, 171(4):453–462, 2014.

[57] Gerald Gartlehner, Bradley N Gaynes, Halle R Amick, Gary N Asher, Laura C Morgan, Emmanuel Coker-Schwimmer, Catherine Forneris, Erin Boland, Linda J Lux, Susan Gaylord, et al. Comparative benefits and harms of antidepressant, psychological, complementary, and exercise treatments for major depression: an evidence report for a clinical practice guideline from the american college of physicians. *Annals of internal medicine*, 164(5):331–341, 2016.

[58] JA Rush, MH Trivedi, SR Wisniewski, AA Nierenberg, JW Stewart, D Warden, M George Niederehe, ME Thase, PW Lavori, BD Lebowitz, et al. Star-d (2006; ajpsych) tiered approach for depression. *Am J Psychiatry*, 163(11):1905–1917, 2006.

[59] Margaret McManus, Patience White, Annie Schmidt, David Kanter, and T Salus. 2020 coding and reimbursement tip sheet for transition from pediatric to adult health care. https://health.maryland.gov/phpa/cyshcn/docs/hctl/2020 [Online; accessed 24-July-2020].

[60] Shinyi Wu, Irene Vidyanti, Pai Liu, Caitlin Hawkins, Magaly Ramirez, Jeffrey Guterman, Sandra Gross-Schulman, Laura Myerchin Sklaroff, and Kathleen Ell. Patient-centered technological assessment and monitoring of depression for low-income patients. *The Journal of Ambulatory Care Management*, 37(2):138, 2014.

[61] American Academy of Sleep Medicine. Evaluation and management services. https://j2vjt3dnbra3ps7ll1clb4q2-wpengine.netdna-ssl.com/wp-content/uploads/2018/11/Eval-Mgmt-payment-RVU-2019.pdf. [Online; accessed 17-April-2020].

[62] James M Russell, Kevin Hawkins, Ronald J Ozminkowski, Lucinda Orsini, William H Crown, Sean Kennedy, Stan Finkelstein, Ernst Berndt, and A John Rush. The cost consequences of treatment-resistant depression. *Journal of Clinical Psychiatry*, 65(3):341–347, 2004.

[63] GoodRx. Prescription Prices. https://www.goodrx.com/go/homepage-lander-sem-7?c=homepage-lander-sem-7&optly_audience=%7bgeoiplogo%7d&utm_campaign=127243741&utm_c
403181980487&gclid=CjwKCAjw04yjBhApEiwAJcvNoVkwdzhq5jQ-vd6xBc7PJBYBUVt9bsr6HcZTZts4mN5dw1kmCp1k1RoCROIQAvD_BwE&gclsrc=aw.ds. [Online; accessed 17-April-2020].

[64] Lara A Treviño, Matthew W Ruble, Kenneth Treviño, Lawrence M Weinstein, and Dana P Gresky. Antidepressant medication prescribing practices for treatment of major depressive disorder. *Psychiatric Services*, 68(2):199–202, 2017.

[65] Spyros Kolovos, Judith E Bosmans, Johanna M van Dongen, Birre van Esveld, Dorcas Magai, Annemieke van Straten, Christina Van Der Feltz-Cornelis, Kirsten M van Steenbergen-Weijenburg, Klaas M Huijbregts, Harm Van Marwijk, et al. Utility scores for different health states related to depression: individual participant data analysis. *Quality of Life Research*, 26:1649–1658, 2017.

[66] Haru Iino, Masayuki Hashiguchi, and Satoko Hori. Estimating the range of incremental cost-effectiveness thresholds for healthcare based on willingness to pay and gdp per capita: A systematic review. *PloS one*, 17(4):e0266934, 2022.

[67] J Todd Auman, Gary A Boorman, Ralph E Wilson, Gregory S Travlos, and Richard S Paules. Heat map visualization of high-density clinical chemistry data. *Physiological genomics*, 31(2):352–356, 2007.

[68] Dmitrij Achelrod, Jonas Schreyögg, and Tom Stargardt. Health-economic evaluation of home telemonitoring for copd in germany: evidence from a large population-based cohort. *The European Journal of Health Economics*, 18:869–882, 2017.

[69] Steven P Dehmer, Michael V Maciosek, Nicole K Trower, Stephen E Asche, Anna R Bergdall, Rachel A Nyboer, Patrick J O'Connor, Pamala A Pawloski, JoAnn M Sperl-Hillen, Beverly B Green, et al. Economic evaluation of the home blood pressure telemonitoring and pharmacist case management to control hypertension (hyperlink) trial. *Journal of the American College of Clinical Pharmacy*, 1(1):21–30, 2018.

[70] Line Bille Madsen, Terkel Christiansen, Peder Kirkegaard, and Erling Bjerregaard Pedersen. Economic evaluation of home blood pressure telemonitoring: a randomized controlled trial. *Blood pressure*, 20(2):117–125, 2011.

[71] Andrew Stoddart, Janet Hanley, Sarah Wild, Claudia Pagliari, Mary Paterson, Steff Lewis, Aziz Sheikh, Ashma Krishan, Paul Padfield, and Brian McKinstry. Telemonitoring-based service redesign for the management of uncontrolled hypertension (hits): cost and cost-effectiveness analysis of a randomised controlled trial. *BMJ open*, 3(5):e002681, 2013.

[72] A Dymond, W Green, E Barker, H Baker, S Dr Thompson-Hilpert, and N Tsitiridis. Ee587 cost-effectiveness of device-based long-term cardiac monitoring in high-risk post-myocardial infarction patients. *Value in Health*, 25(12):S171, 2022.

[73] William S Weintraub and David J Cohen. The limits of cost-effectiveness analysis. *Circulation: Cardiovascular Quality and Outcomes*, 2(1):55–58, 2009.

[74] Brooke Levis, Andrea Benedetti, and Brett D Thombs. Accuracy of patient health questionnaire-9 (phq-9) for screening to detect major depression: individual participant data meta-analysis. *bmj*, 365, 2019.

[75] Aruna Chandran, Adnan A Hyder, and Corinne Peek-Asa. The global burden of unintentional injuries and an agenda for progress. *Epidemiologic reviews*, 32(1):110–120, 2010.

[76] World Health Organization et al. Violence, injuries and disability biennial report, 2006-2007. https://iris.who.int/bitstream/handle/10665/43955/9789241597081_eng.pdf, 2008. [Online; accessed 24-Jul-2023].

[77] Brian Celso, Joseph Tepas, Barbara Langland-Orban, Etienne Pracht, Linda Papa, Lawrence Lottenberg, and Lewis Flint. A systematic review and meta-analysis comparing outcome of severely injured patients treated in trauma centers following the establishment of trauma systems. *Journal of Trauma and Acute Care Surgery*, 60(2):371–378, 2006.

[78] Lynne Moore, Henry Thomas Stelfox, David Evans, Sayed Morad Hameed, Natalie L Yanchar, Richard Simons, John Kortbeek, Gilles Bourgeois, Julien Clément, Alexis F Turgeon, et al. Trends in injury outcomes across canadian trauma systems. *JAMA surgery*, 152(2):168–174, 2017.

[79] Melanie J Zimmer-Gembeck, Patricia A Southard, Jerris R Hedges, Richard J Mullins, Donna Rowland, Judith Veum Stone, and Donald D Trunkey. Triage in an established trauma system. *Journal of Trauma and Acute Care Surgery*, 39(5):922–928, 1995.

[80] Demetrios Demetriades, Mathew Martin, Ali Salim, Peter Rhee, Carlos Brown, and Linda Chan. The effect of trauma center designation and trauma volume on outcome in specific severe injuries. *Annals of surgery*, 242(4):512, 2005.

[81] Charles A Goldfarb, Joseph Borrelli Jr, Michael Lu, and William M Ricci. A prospective evaluation of patients with isolated orthopedic injuries transferred to a level i trauma center. *Journal of orthopaedic trauma*, 20(9):613–617, 2006.

[82] State of Reform. Does Washington need more trauma hospitals? https://stateofreform.com/news/washington/2021/12/does-washington-need-more-trauma-hospitals/. [Online; accessed 7-May-2023].

[83] Joshua B Brown, Gregory A Watson, Raquel M Forsythe, Louis H Alarcon, Graciela Bauza, Alan D Murdock, Timothy R Billiar, Andrew B Peitzman, and Jason L Sperry. American college of surgeons trauma center verification versus state designation: are level ii centers slipping through the cracks? *The journal of trauma and acute care surgery*, 75(1):44, 2013.

[84] Avery B Nathens, Gregory J Jurkovich, Frederick P Rivara, and Ronald V Maier. Effectiveness of state trauma systems in reducing injury-related mortality: a national evaluation. *Journal of Trauma and Acute Care Surgery*, 48(1):25, 2000.

[85] Kenneth J Koval, Chad W Tingey, and Kevin F Spratt. Are patients being transferred to level-i trauma centers for reasons other than medical necessity? *JBJS*, 88(10):2124–2132, 2006.

[86] Montri D Wongworawat, Gary Capistrant, and John M Stephenson. The opportunity awaits to lead orthopaedic telehealth innovation: Aoa critical issues. *JBJS*, 99(17):e93, 2017.

[87] Lynne Moore, Brahim Cisse, Brice Lionel Batomen Kuimi, Henry T Stelfox, Alexis F Turgeon, François Lauzier, Julien Clément, and Gilles Bourgeois. Impact of socio-economic status on hospital length of stay following injury: a multicenter cohort study. *BMC health services research*, 15(1):1–9, 2015.

[88] Sage R Myers, Charles C Branas, Benjamin French, Michael L Nance, and Brendan G Carr. A national analysis of pediatric trauma care utilization and outcomes in the united states. *Pediatric emergency care*, 35(1):1, 2019.

[89] Washington State Department of Health. Comprehensive Hospital Abstract Reporting System (CHARS). https://doh.wa.gov/data-statistical-reports/healthcare-washington/hospital-and-patient-data/hospital-discharge-data-chars. [Online; accessed 2-May-2023].

[90] Washington State Department of Health. Washington state department of health trauma services. https://doh.wa.gov/sites/default/files/2022-02/530101.pdf. [Online; accessed 2-May-2023].

[91] Agency for Healthcare Research and Quality. Hcup - procedure classes refined for icd-10-pcs. https://hcup-us.ahrq.gov/toolssoftware/procedureicd10/procedure_icd10.jsp. [Online; accessed 11-May-2023].

[92] Wikipedia. Diagnosis-related group. https://en.wikipedia.org/wiki/Diagnosis-related_group. [Online; accessed 11-May-2023].

[93] Agency for Healthcare Research and Quality. Hcup - clinical classifications software (ccs) for icd-10-pcs (beta version). https://hcup-us.ahrq.gov/toolssoftware/ccs10/ccs10.jsp. [Online; accessed 11-May-2023].

[94] Wikipedia. Abbreviated injury scale. https://en.wikipedia.org/wiki/Abbreviated_Injury_Scale. [Online; accessed 11-May-2023].

[95] David E Clark, Adam W Black, David H Skavdahl, and Lee D Hallagan. Open-access programs for injury categorization using icd-9 or icd-10. *Injury epidemiology*, 5:1–8, 2018.

[96] Association for the Advancement of Automotive Medicine. Abbreviated injury scale. https://www.aaam.org/abbreviated-injury-scale-ais/. [Online; accessed 11-May-2023].

[97] Wikipedia. Icd-10-cm. https://en.wikipedia.org/wiki/ICD-10-CM#: :text=The%20ICD%2D10%20Clinical%20Modification,earlier%20ICD%2D9%2DCM. [Online; accessed 11-May-2023].

[98] American College of Surgeons. National trauma data standard (ntds). https://www.facs.org/quality-programs/trauma/quality/national-trauma-data-bank/national-trauma-data-standard/. [Online; accessed 11-May-2023].

[99] Wikipedia. Injury severity score. https://en.wikipedia.org/wiki/Injury_Severity_Score. [Online; accessed 11-May-2023].

[100] M LeMier, P Cummings, and Theresa A West. Accuracy of external cause of injury codes reported in washington state hospital discharge records. *Injury Prevention*, 7(4):334–338, 2001.

[101] ATSDR (Agency for Toxic Substances and Disease Registry). Cdc/atsdr svi data and documentation download. https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html. [Online; accessed 11-May-2023].

[102] Robert Graham Center. Social deprivation index (sdi). https://www.graham-center.org/maps-data-tools/social-deprivation-index.html. [Online; accessed 11-May-2023].

[103] Markus Ringnér. What is principal component analysis? *Nature biotechnology*, 26(3):303–304, 2008.

[104] Alan P Reynolds, Graeme Richards, and Vic J Rayward-Smith. The application of k-medoids and pam to the clustering of rules. In *Intelligent Data Engineering and Automated Learning–IDEAL 2004: 5th International Conference, Exeter, UK. August 25-27, 2004. Proceedings 5*, pages 173–178. Springer, 2004.

[105] Michael E Wall, Andreas Rechtsteiner, and Luis M Rocha. Singular value decomposition and principal component analysis. *A practical approach to microarray data analysis*, pages 91–109, 2003.

[106] Sarah Majercik, Robert Z Tashjian, Walter L Biffl, David T Harrington, and William G Cioffi. Halo vest immobilization in the elderly: a death sentence? *Journal of Trauma and Acute Care Surgery*, 59(2):350–357, 2005.

[107] Tabitha Garwe, Kenneth E Stewart, Craig D Newgard, Julie A Stoner, John C Sacra, Patrick Cody, Babawale Oluborode, and Roxie M Albrecht. Survival benefit of treatment at or transfer to a tertiary trauma center among injured older adults. *Prehospital Emergency Care*, 24(2):245–256, 2020.

[108] Christopher Spering, Rolf Lefering, Bertil Bouillon, Wolfgang Lehmann, Kajetan von Eckardstein, Klaus Dresing, and Stephan Sehmisch. It is time for a change in the management of elderly severely injured patients! an analysis of 126,015 patients from the traumaregister dgu®. *European journal of trauma and emergency surgery*, 46:487–497, 2020.

[109] Sunjay Sharma, Des Bohn, Iphigenia Mikroyiannakis, Joslyn Trowbridge, Donna Thompson, Robert Bell, and James Rutka. Development of a multi stakeholder partnership to improve access to and delivery of neurosurgical services in ontario. *Health Policy*, 121(2):207–214, 2017.

[110] Alicia Gaidry Sykes. *Pediatric trauma in the California-Mexico border region: injury disparities by Area Deprivation Index*. University of California, San Diego, 2021.

[111] Pia Kjær Kristensen, Anne Mette Falstie-Jensen, Morten Madsen, and Søren Paaske Johnsen. Patient-related healthcare disparities in the quality of acute hip fracture care: a 10-year nationwide population-based cohort study. *BMJ open*, 11(12):e051424, 2021.

[112] Jennings H Dooley, Esra Ozdenerol, John P Sharpe, Louis J Magnotti, Martin A Croce, and Peter E Fischer. Location, location, location: utilizing needs-based assessment of trauma systems-2 in trauma system planning. *Journal of trauma and acute care surgery*, 88(1):94–100, 2020.

[113] Ellen J MacKenzie, Frederick P Rivara, Gregory J Jurkovich, Avery B Nathens, Katherine P Frey, Brian L Egleston, David S Salkever, and Daniel O Scharfstein. A national evaluation of the effect of trauma-center care on mortality. *New England Journal of Medicine*, 354(4):366–378, 2006.

[114] Avery B Nathens, Gregory J Jurkovich, Ronald V Maier, David C Grossman, Ellen J MacKenzie, Maria Moore, and Frederick P Rivara. Relationship between trauma center volume and outcomes. *Jama*, 285(9):1164–1171, 2001.

[115] Donald Berwick, Autumn Downey, and Elizabeth Cornett. *A national trauma care system: integrating military and civilian trauma systems to achieve zero preventable deaths after injury*. National Academies Press (US), 2016.

[116] MF Rotondo, C Cribari, RS Smith, American College of Surgeons Committee on Trauma, et al. Resources for optimal care of the injured patient. *Chicago: American College of Surgeons*, 6, 2014.

[117] Garth H Utter, Ronald V Maier, Frederick P Rivara, Charles N Mock, Gregory J Jurkovich, and Avery B Nathens. Inclusive trauma systems: do they improve triage or outcomes of the severely injured? *Journal of Trauma and Acute Care Surgery*, 60(3):529–537, 2006.

[118] RL Gruen, BJ Gabbe, HT Stelfox, and Peter A Cameron. Indicators of the quality of trauma care and the performance of trauma systems. *Journal of British Surgery*, 99(Supplement_1):97–104, 2012.

[119] American College of Surgeons Committee on Trauma. Trauma System Consultation Report - State of Washington. https://static1.squarespace.com/static/596961652e69cffedda490b9/t/5d5d9624b67f5f0001d2705d/1566414377279/Full+Report.pdf. [Online; accessed 8-May-2023].

[120] Henry Thomas Stelfox, Barbara Bobranska-Artiuch, Avery Nathens, and Sharon E Straus. Quality indicators for evaluating trauma care: a scoping review. *Archives of Surgery*, 145(3):286–295, 2010.

[121] Joseph Utecht, Jane Ball, Stephen M Bowman, Jimm Dodd, John Judkins, Robert T Maxson, Rosemary Nabaweesi, Rohit Pradhan, Nels D Sanddal, Robert J Winchell, et al. Development and validation of a controlled vocabulary: An owl representation of organizational structures of trauma centers and trauma systems. *Studies in health technology and informatics*, 264:403, 2019.

[122] Jia-Hong Tang, Yen-Hui Chiu, Po-Huang Chiang, Ming-Daw Su, and Ta-Chien Chan. A flow-based statistical model integrating spatial and nonspatial dimensions to measure healthcare access. *Health & Place*, 47:126–138, 2017.

[123] Omar K Danner, L Ray Matthews, Kenneth L Wilson, and Sheryl L Heron. Healthcare outcome disparities in trauma care. *Western Journal of Emergency Medicine*, 13(3):217, 2012.

[124] Alexandra C Ferre, Jacqueline Curtis, J Alford Flippin, Jeffrey A Claridge, Esther S Tseng, Laura R Brown, and Vanessa Phillis Ho. Do new trauma centers provide needed or redundant access? a nationwide analysis. *Journal of Trauma and Acute Care Surgery*, 93(3):347–352, 2022.

[125] Joni Strom Williams, Rebekah J Walker, and Leonard E Egede. Achieving equity in an evolving healthcare system: opportunities and challenges. *The American journal of the medical sciences*, 351(1):33–43, 2016.

[126] Daniel A Alber, Michael K Dalton, Tarsicio Uribe-Leitz, Gezzer Ortega, Ali Salim, Adil H Haider, and Molly P Jarman. A multistate study of race and ethnic disparities in access to trauma care. *Journal of Surgical Research*, 257:486–492, 2021.

[127] Brendan G Carr, Ariel J Bowman, Catherine S Wolff, Michael T Mullen, Daniel N Holena, Charles C Branas, and Douglas J Wiebe. Disparities in access to trauma care in the united states: a population-based analysis. *Injury*, 48(2):332–338, 2017.

[128] Adil H Haider, David C Chang, David T Efron, Elliott R Haut, Marie Crandall, and Edward E Cornwell. Race and insurance status as risk factors for trauma mortality. *Archives of Surgery*, 143(10):945–949, 2008.

[129] Adil H Haider, David T Efron, Elliott R Haut, Stephen M DiRusso, Thomas Sullivan, and Edward E Cornwell III. Black children experience worse clinical and functional outcomes after traumatic brain injury: an analysis of the national pediatric trauma registry. *Journal of Trauma and Acute Care Surgery*, 62(5):1259–1263, 2007.

[130] Caitlin W Hicks, Zain G Hashmi, Catherine Velopulos, David T Efron, Eric B Schneider, Elliott R Haut, Edward E Cornwell, and Adil H Haider. Association between race and age in survival after trauma. *JAMA surgery*, 149(7):642–647, 2014.

[131] Ajay Premkumar, Andrew Zhu, Xiaohan Ying, Christian A Pean, Neil P Sheth, Michael B Cross, and Alejandro Gonzalez Della Valle. The interconnected ancestral network of hip arthroplasty device approval. *JAAOS-Journal of the American Academy of Orthopaedic Surgeons*, 29(24):e1362–e1369, 2021.

[132] Ezzatollah Asgharizadeh, Mahsa Kadivar, Mohammad Noroozi, Vahid Mottaghi, Hamed Mohammadi, and Adel Pourghader Chobar. The intelligent traffic management system for emergency medical service station location and allocation of ambulances. *Computational intelligence and neuroscience*, 2022, 2022.

[133] Farshad Majzoubi, Lihui Bai, and Sunderesh S Heragu. An optimization approach for dispatching and relocating ems vehicles. *IIE Transactions on Healthcare Systems Engineering*, 2(3):211–223, 2012.

[134] Justin J Boutilier and Timothy CY Chan. Ambulance emergency response optimization in developing countries. *Operations Research*, 68(5):1315–1334, 2020.

[135] Adel Hatami-Marbini, Nilofar Varzgani, Seyed Mojtaba Sajadi, and Ahmad Kamali. An emergency medical services system design using mathematical modeling and simulation-based optimization approaches. *Decision Analytics Journal*, 3:100059, 2022.

[136] Sagarkumar Hirpara, Monit Vaishnav, Pratik J Parikh, Nan Kong, and Priti Parikh. Locating trauma centers considering patient safety. *Health care management science*, 25(2):291–310, 2022.

[137] Soo-Haeng Cho, Hoon Jang, Taesik Lee, and John Turner. Simultaneous location of trauma centers and helicopters for emergency medical service planning. *Operations Research*, 62(4):751–771, 2014.

[138] Jan O Jansen, Jonathan J Morrison, Handing Wang, Robin Lawrenson, Gerry Egan, Shan He, and Marion K Campbell. Optimizing trauma system design: the geos (geospatial evaluation of systems of trauma care) approach. *Journal of Trauma and Acute Care Surgery*, 76(4):1035–1040, 2014.

[139] Federico Coccolini, Yoram Kluger, Ernest E Moore, Ronald V Maier, Raul Coimbra, Carlos Ordoñez, Rao Ivatury, Andrew W Kirkpatrick, Walter Biffl, Massimo Sartelli, et al. Trauma quality indicators: internationally approved core factors for trauma management quality evaluation. *World journal of emergency surgery*, 16:1–10, 2021.

[140] American College of Surgeons. Resources for Optimal Care of the Injured Patient. https://www.facs.org/quality-programs/trauma/quality/verification-review-and-consultation-program/standards/. [Online; accessed 24-Jul-2024].

[141] American College of Surgeons. ACS Trauma Quality Programs - Best Practices Guidelines for Acute Pain Management in Trauma Patients. https://www.facs.org/media/exob3dwk/acute_pain_guidelines.pdf. [Online; accessed 24-Jul-2024].

[142] American College of Surgeons. ACS TQIP Geriatric Trauma Management Guidelines. https://www.facs.org/media/rddahzbb/geriatric_guidelines.pdf. [Online; accessed 24-Jul-2024].

[143] American College of Surgeons. ACS TQIP Best Practices Guidelines in Imaging. https://www.facs.org/media/oxdjw5zj/imaging_guidelines.pdf. [Online; accessed 24-Jul-2024].

[144] American College of Surgeons. ACS TQIP Best Practices in the Management of Orthopaedic Trauma. https://www.facs.org/media/mkbnhqtw/ortho_guidelines.pdf. [Online; accessed 24-Jul-2024].

[145] American College of Surgeons. Trauma Quality Programs - Best Practices Guidelines Spine Injury. https://www.facs.org/media/k45gikqv/spine_injury_guidelines.pdf. [Online; accessed 24-Jul-2024].

[146] American College of Surgeons. ACS TQIP Best Practices in the Management of Traumatic Brain Injury. https://www.facs.org/media/mkej5u3b/tbi_guidelines.pdf. [Online; accessed 24-Jul-2024].

[147] American College of Surgeons. ACS TQIP Massive Transfusion in Trauma Guidelines. https://www.facs.org/media/zcjdtrd1/transfusion_guildelines.pdf. [Online; accessed 24-Jul-2024].

[148] Nancy Carney, Annette M Totten, Cindy O'Reilly, Jamie S Ullman, Gregory WJ Hawryluk, Michael J Bell, Susan L Bratton, Randall Chesnut, Odette A Harris, Niranjan Kissoon, et al. Guidelines for the management of severe traumatic brain injury. *Neurosurgery*, 80(1):6–15, 2017.

[149] Patrick M Kochanek, Robert C Tasker, Nancy Carney, Annette M Totten, P David Adelson, Nathan R Selden, Cynthia Davis-O'Reilly, Erica L Hart, Michael J Bell, Susan L Bratton, et al. Guidelines for the management of pediatric severe traumatic brain injury: update of the brain trauma foundation guidelines. *Pediatric Critical Care Medicine*, 20(3S):S1–S82, 2019.

[150] M Ross Bullock, Randall Chesnut, Jamshid Ghajar, David Gordon, Roger Hartl, David W Newell, Franco Servadei, Beverly C Walters, and Jack E Wilberger. Guidelines for the surgical management of traumatic brain injury author group: acknowledgments. *Neurosurgery*, 58(3):S2–vi, 2006.

[151] Neeraj Badjatia, Nancy Carney, Todd J Crocco, Mary Elizabeth Fallat, Halim MA Hennes, Andrew S Jagoda, Sarah Jernigan, Peter B Letarte, E Brooke Lerner, Thomas M Moriarty, et al. Guidelines for prehospital management of traumatic brain injury 2nd edition. *Prehospital emergency care*, 12(sup1):S1–S52, 2008.

[152] Nicole Fox, Diane Schwartz, Jose H Salazar, Elliott R Haut, Philipp Dahm, James H Black, Scott C Brakenridge, John J Como, Kimberly Hendershot, David R King, et al. Evaluation and management of blunt traumatic aortic injury: a practice management guideline from the eastern association for the surgery of trauma. *Journal of Trauma and Acute Care Surgery*, 78(1):136–146, 2015.

[153] Abenamar Arrillaga. Practice management guidelines for penetrating trauma to the lower extremity. *EAST practice management work group. Eastern Association for the Surgery of Trauma*, 2000.

[154] Jeremy W Cannon, Mansoor A Khan, Ali S Raja, Mitchell J Cohen, John J Como, Bryan A Cotton, Joseph J Dubose, Erin E Fox, Kenji Inaba, Carlos J Rodriguez, et al. Damage control resuscitation in patients with severe traumatic hemorrhage: a practice management guideline from the eastern association for the surgery of trauma. *Journal of Trauma and Acute Care Surgery*, 82(3):605–617, 2017.

[155] John J Como, Jose J Diaz, C Michael Dunham, William C Chiu, Therese M Duane, Jeannette M Capella, Michele R Holevar, Kosar A Khwaja, Julie A Mayglothling, Michael B Shapiro, et al. Practice management guidelines for identification of cervical spine injuries following trauma: update from the eastern association for the surgery of trauma practice management guidelines committee. *Journal of Trauma and Acute Care Surgery*, 67(3):651–659, 2009.

[156] David G Jacobs, Brian Ray Plaisier, Philip S Barie, Jeffrey S Hammond, Michele R Holevar, Karlene E Sinclair, Thomas M Scalea, Wendy Wahl, EAST Practice Management Guidelines Work Group, et al. Practice management guidelines for geriatric trauma: the east practice management guidelines work group. *Journal of Trauma and Acute Care Surgery*, 54(2):391–416, 2003.

[157] John J Como, Faran Bokhari, William C Chiu, Therese M Duane, Michele R Holevar, Margaret A Tandoh, Rao R Ivatury, and Thomas M Scalea. Practice management

guidelines for selective nonoperative management of penetrating abdominal trauma. *Journal of Trauma and Acute Care Surgery*, 68(3):721–733, 2010.

[158] William S Hoff, John A Bonadies, Riad Cachecho, and Warren C Dorlac. East practice management guidelines work group: update to practice management guidelines for prophylactic antibiotic use in open fractures. *Journal of Trauma and Acute Care Surgery*, 70(3):751–754, 2011.

[159] Robert D Barraco, William C Chiu, Thomas V Clancy, John J Como, James B Ebert, L Wayne Hess, William S Hoff, Michele R Holevar, J Gerald Quirk, Bruce J Simon, et al. Practice management guidelines for the diagnosis and management of injury in the pregnant patient: the east practice management guidelines work group. *Journal of Trauma and Acute Care Surgery*, 69(1):211–214, 2010.

[160] Julie Mayglothling, Therese M Duane, Michael Gibbs, Maureen McCunn, Eric Legome, Alexander L Eastman, James Whelan, and Kaushal H Shah. Emergency tracheal intubation immediately following traumatic injury: an eastern association for the surgery of trauma practice management guideline. *Journal of Trauma and Acute Care Surgery*, 73(5):S333–S340, 2012.

[161] Ronald R Barbosa, Randeep Jawa, Jennifer M Watters, Jennifer C Knight, Andrew J Kerwin, Eleanor S Winston, Robert D Barraco, Brian Tucker, James M Bardes, and Susan E Rowell. Evaluation and management of mild traumatic brain injury: an eastern association for the surgery of trauma practice management guideline. *Journal of Trauma and Acute Care Surgery*, 73(5):S307–S314, 2012.

[162] Nicole Fox, Ravi R Rajani, Faran Bokhari, William C Chiu, Andrew Kerwin, Mark J Seamon, David Skarupa, and Eric Frykberg. Evaluation and management of penetrating lower extremity arterial trauma: an eastern association for the surgery of trauma practice management guideline. *Journal of Trauma and Acute Care Surgery*, 73(5):S315–S320, 2012.

[163] Rajesh R Gandhi, Tiffany L Overton, Elliott R Haut, Brandyn Lau, Heather A Vallier, Thomas Rohs, Erik Hasenboehler, Jane Kayle Lee, Darrell Alley, Jennifer Watters, et al. Optimal timing of femur fracture stabilization in polytrauma patients: A practice management guideline from the eastern association for the surgery of trauma. *Journal of Trauma and Acute Care Surgery*, 77(5):787–795, 2014.

[164] SA Tisherman, F Bokhari, B Collier, et al. Clinical practice guidelines: Penetrating neck trauma. chicago: Eastern association for the surgery of trauma, 2008.

[165] Catherine G Velopulos, Hasan M Shihab, Lawrence Lottenberg, Marcie Feinman, Ali Raja, Jeffrey Salomone, and Elliott R Haut. Prehospital spine immobilization/spinal motion restriction in penetrating trauma: A practice management guideline from the eastern association for the surgery of trauma (east). *Journal of Trauma and Acute Care Surgery*, 84(5):736–744, 2018.

[166] Sherry Sixta, Forrest O Moore, Michael F Ditillo, Adam D Fox, Alejandro J Garcia, Daniel Holena, Bellal Joseph, Leslie Tyrie, and Bryan Cotton. Screening for thoracolumbar spinal injuries in blunt trauma: an eastern association for the surgery of trauma practice management guideline. *Journal of Trauma and Acute Care Surgery*, 73(5):S326–S332, 2012.

[167] Nicole A Stassen, Indermeet Bhullar, Julius D Cheng, Marie L Crandall, Randall S Friese, Oscar D Guillamondegui, Randeep S Jawa, Adrian A Maung, Thomas J Rohs Jr, Ayodele Sangosanya, et al. Selective nonoperative management of blunt splenic injury: an eastern association for the surgery of trauma practice management guideline. *Journal of Trauma and Acute Care Surgery*, 73(5):S294–S300, 2012.

[168] Mark J Seamon, Elliott R Haut, Kyle Van Arendonk, Ronald R Barbosa, William C Chiu, Christopher J Dente, Nicole Fox, Randeep S Jawa, Kosar Khwaja, J Kayle Lee, et al. An evidence-based approach to patient selection for emergency department thoracotomy: a practice management guideline from the eastern association for the surgery of trauma. *Journal of Trauma and Acute Care Surgery*, 79(1):159–173, 2015.

[169] Nikolay Bugaev, John J Como, Guy Golani, Jennifer J Freeman, Jaswin S Sawhney, Cory J Vatsaas, Brian K Yorkgitis, Laura A Kreiner, Nicole M Garcia, Hiba Abdel Aziz, et al. Thromboelastography and rotational thromboelastometry in bleeding patients with coagulopathy: Practice management guideline from the eastern association for the surgery of trauma. *Journal of Trauma and Acute Care Surgery*, 89(6):999–1017, 2020.

[170] Deborah B Diercks, Abhishek Mehrotra, Devorah J Nazarian, Susan B Promes, Wyatt W Decker, and Francis M Fesmire. Clinical policy: critical issues in the evaluation of adult patients presenting to the emergency department with acute blunt abdominal trauma. *Annals of emergency medicine*, 57(4):387–404, 2011.

[171] Jonathan H Valente, John D Anderson, William F Paolo, Kelly Sarmiento, Christian A Tomaszewski, MBA Jason S Haukoos, Deborah B Diercks, Richard Byyny, Christopher R Carpenter, Benjamin Friedman, et al. Clinical policy: Critical issues in the management of adult patients presenting to the emergency department with mild traumatic brain injury. *Ann Emerg Med*, 81:63–83, 2023.

[172] Marianne Gausche-Hill, Kathleen M Brown, Zoë J Oliver, Comilla Sasson, Peter S Dayan, Nicholas M Eschmann, Tasmeen S Weik, Benjamin J Lawner, Ritu Sahni, Yngve Falck-Ytter, et al. An evidence-based guideline for prehospital analgesia in trauma. *Prehospital Emergency Care*, 18(sup1):25–34, 2014.

[173] Diane M. Sobieraj, William L. Baker, Brandon K. Martinez, et al. *Comparative Effectiveness of Analgesics To Reduce Acute Pain in the Prehospital Setting*. Comparative Effectiveness Review, No. 220. Agency for Healthcare Research and Quality (US), Rockville (MD), September 2019. Available from: https://www.ncbi.nlm.nih.gov/books/NBK546202/.

[174] Nancy Carney, Tyson Cheney, Ann M. Totten, et al. *Prehospital Airway Management: A Systematic Review*. Comparative Effectiveness Review, No. 243. Agency for Healthcare Research and Quality (US), Rockville (MD), June 2021. Available from: https://www.ncbi.nlm.nih.gov/books/NBK571440/, doi: 10.23970/AHRQEPCCER243.

[175] Eileen M Bulger, David Snyder, Karen Schoelles, Cathy Gotschall, Drew Dawson, Eddy Lang, Nels D Sanddal, Frank K Butler, Mary Fallat, Peter Taillac, et al. An evidence-based prehospital guideline for external hemorrhage control: American college of surgeons committee on trauma. *Prehospital Emergency Care*, 18(2):163–173, 2014.

[176] National Highway Traffic Safety Administration Office of Emergency Medical Services. Progress on Evidence-Based Guidelines For Prehospital Emergency Care. https://www.ems.gov/assets/EBG_for_Prehospital_Care-1663305752.pdf. [Online; accessed 24-Jul-2024].

[177] Craig D Newgard, Peter E Fischer, Mark Gestring, Holly N Michaels, Gregory J Jurkovich, E Brooke Lerner, Mary E Fallat, Theodore R Delbridge, Joshua B Brown, Eileen M Bulger, et al. National guideline for the field triage of injured patients: recommendations of the national expert panel on field triage, 2021. *Journal of Trauma and Acute Care Surgery*, 93(2):e49–e60, 2022.

[178] Pennsylvania Trauma System Foundation (PTSF). Pennsylvania Trauma System Foundation Trauma Registry. https://www.ptsf.org/trauma-registry/. [Online; accessed 21-Jul-2024].

[179] Hertzel C Gerstein, Chinthanie Ramasundarahettige, and Shrikant I Bangdiwala. Creating composite indices from continuous variables for research: the geometric mean. *Diabetes Care*, 44(5):e85–e86, 2021.

[180] Takashi Izutsu, Atsuro Tsutsumi, Harry Minas, Graham Thornicroft, Vikram Patel, and Akiko Ito. Mental health and wellbeing in the sustainable development goals. *The Lancet Psychiatry*, 2(12):1052–1054, 2015.

[181] G Roth. Global burden of disease collaborative network. global burden of disease study 2017 (gbd 2017) results. seattle, united states: Institute for health metrics and evaluation (ihme), 2018. *The Lancet*, 392:1736–88, 2018.

[182] UNDP. Technical notes: Calculating the human development indices. https://hdr.undp.org/sites/default/files/2021-22_HDR/hdr2021-22_technical_notes.pdf. [Online; accessed 24-Jul-2024].

[183] Joint Research Centre-European Commission et al. *Handbook on constructing composite indicators: methodology and user guide*. OECD publishing, 2008.

[184] Qingyuan Xue, Yancun Fan, Junjie Wang, Yuanyuan Kuang, and Yingsong Chen. An optimization model and computer simulation for allocation planning of hospital bed resources. *Mathematical Problems in Engineering*, 2022, 2022.

[185] Peshawa Jamal Muhammad Ali, Rezhna Hassan Faraj, Erbil Koya, Peshawa J Muhammad Ali, and Rezhna H Faraj. Data normalization and standardization: a technical report. *Mach Learn Tech Rep*, 1(1):1–6, 2014.

[186] Ian T Jolliffe. *Principal component analysis for special types of data*. Springer, 2002.

[187] Vijaya Krishnan. Constructing an area-based socioeconomic index: A principal components analysis approach. *Edmonton, Alberta: Early Child Development Mapping Project*, 2010.

[188] Grace Maria Antony and K Visweswara Rao. A composite index to explain variations in poverty, health, nutritional status and standard of living: Use of multivariate statistical methods. *Public Health*, 121(8):578–587, 2007.

[189] William L Hightower. Development of an index of health utilizing factor analysis. *Medical care*, 16(3):245–255, 1978.

[190] C Chandra Sekhar, Abhaya Indrayan, and SM Gupta. Development of an index of need for health resources for indian states using factor analysis. *International journal of epidemiology*, 20(1):246–250, 1991.

[191] Garima Srivastava and Pradeep Kumar. Water quality index with missing parameters. *International Journal of research in Engineering and Technology*, 2(4):609–614, 2013.

[192] Shiran Rachmilevitch. Egalitarianism, utilitarianism, and the nash bargaining solution. *Social Choice and Welfare*, 52(4):741–751, 2019.

[193] Andreu Mas-Colell, Michael Dennis Whinston, Jerry R Green, et al. *Microeconomic theory*, volume 1. Oxford university press New York, 1995.

[194] H Peyton Young. *Equity: in theory and practice*. Princeton University Press, 1995.

[195] Alan Williams and Richard Cookson. Equity in health. *Handbook of health economics*, 1:1863–1910, 2000.

[196] Jeonghoon Mo and Jean Walrand. Fair end-to-end window-based congestion control. *IEEE/ACM Transactions on networking*, 8(5):556–567, 2000.

[197] Jessica H McCoy and Hau L Lee. Using fairness models to improve equity in health delivery fleet management. *Production and Operations Management*, 23(6):965–977, 2014.

[198] Andreas Maurer, Daniela Angela Parletta, Andrea Paudice, and Massimiliano Pontil. Robust unsupervised learning via l-statistic minimization. In *International Conference on Machine Learning*, pages 7524–7533. PMLR, 2021.

[199] Robert J Serfling. *Approximation theorems of mathematical statistics*, volume 162. John Wiley & Sons, 2009.

[200] Galen R Shorack and GR Shorack. *Probability for statisticians*, volume 951. Springer, 2000.

[201] Justin Khim, Liu Leqi, Adarsh Prasad, and Pradeep Ravikumar. Uniform convergence of rank-weighted learning. In *International Conference on Machine Learning*, pages 5254–5263. PMLR, 2020.

[202] Yanbo Fan, Siwei Lyu, Yiming Ying, and Baogang Hu. Learning with average top-k loss. *Advances in neural information processing systems*, 30, 2017.

[203] Matthew J Holland and El Mehdi Haress. Spectral risk-based learning using unbounded losses. In *International Conference on Artificial Intelligence and Statistics*, pages 1871–1886. PMLR, 2022.

[204] Kenji Kawaguchi and Haihao Lu. Ordered sgd: A new stochastic optimization framework for empirical risk minimization. In *International Conference on Artificial Intelligence and Statistics*, pages 669–679. PMLR, 2020.

[205] Jaeho Lee, Sejun Park, and Jinwoo Shin. Learning bounds for risk-sensitive learning. *Advances in Neural Information Processing Systems*, 33:13867–13879, 2020.

[206] Liu Leqi, Adarsh Prasad, and Pradeep K Ravikumar. On human-aligned risk minimization. *Advances in Neural Information Processing Systems*, 32, 2019.

[207] Robert Williamson and Aditya Menon. Fairness risk measures. In *International Conference on Machine Learning*, pages 6786–6797. PMLR, 2019.

[208] Ronak Mehta, Vincent Roulet, Krishna Pillutla, Lang Liu, and Zaid Harchaoui. Stochastic optimization for spectral risk measures. In Francisco Ruiz, Jennifer Dy, and Jan-Willem van de Meent, editors, *Proceedings of The 26th International Conference on Artificial Intelligence and Statistics*, volume 206 of *Proceedings of Machine Learning Research*, pages 10112–10159. PMLR, 25–27 Apr 2023.

[209] Michele Conforti, Gérard Cornuéjols, Giacomo Zambelli, et al. *Integer programming*, volume 271. Springer, 2014.

[210] Adam G Elshaug, Meredith B Rosenthal, John N Lavis, Shannon Brownlee, Harald Schmidt, Somil Nagpal, Peter Littlejohns, Divya Srivastava, Sean Tunis, and Vikas Saini. Levers for addressing medical underuse and overuse: achieving high-value health care. *The Lancet*, 390(10090):191–202, 2017.

[211] Asha Devereaux, Holly Yang, Gilbert Seda, Viji Sankar, Ryan C Maves, Navaz Karanjia, John Scott Parrish, Christy Rosenberg, Paula Goodman-Crews, Lynette Cederquist, et al. Optimizing scarce resource allocation during covid-19: rapid creation of a regional health-care coalition and triage teams in san diego county, california. *Disaster medicine and public health preparedness*, 16(1):321–327, 2022.

[212] Charles C Branas, Ellen J MacKenzie, and Charles S ReVelle. A trauma resource allocation model for ambulances and hospitals. *Health services research*, 35(2):489, 2000.

[213] Joaquín A Pacheco and Silvia Casado. Solving two location models with few facilities by using a hybrid heuristic: a real health resources case. *Computers & operations research*, 32(12):3075–3091, 2005.

[214] Paul M Griffin, Christina R Scherrer, and Julie L Swann. Optimization of community health center locations and service offerings with statistical need estimation. *IIE transactions*, 40(9):880–892, 2008.

[215] H Shavandi and H Mahlooji. Fuzzy hierarchical queueing models for the location set covering problem in congested systems. *Scientia Iranica*, 15(3), 2008.

[216] Office of policy development and research (PD&R). Hud usps zip code crosswalk files. https://www.huduser.gov/portal/datasets/usps_crosswalk.html. [Online; accessed 14-May-2023].

[217] Ismail Bin Mohamad and Dauda Usman. Standardization and its effects on k-means clustering algorithm. *Research Journal of Applied Sciences, Engineering and Technology*, 6(17):3299–3303, 2013.

[218] Peter J Rousseeuw. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics*, 20:53–65, 1987.

[219] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(11), 2008.

Appendix A

APPENDIX OF CHAPTER 2

A.1 Supplement on Model Input Parameters

A.1.1 Background mortality and hazard ratio

the 2017 U.S. Centers for Disease Control (CDC) life tables [55]. We computed a weighted mortality rate based on the sex distribution of our simulated population in the base case. Patients with depression have a higher risk of death, thus we multiplied the mortality rates by the hazard ratios of 1.59, 1.52, and 1.45 for depression levels S, M, and H, respectively [56]. In the sensitivity analysis, we assumed a 70% lower bound and a 130% upper bound.

A.1.2 Follow-up and treatment discontinuation

We assumed there are two types of discontinuations: follow-up discontinuation and treatment discontinuation. They add up to be the total discontinuation [51, 57]. Follow-up discontinuation stands for the probability that the patient has not gone to the follow-up appointment as scheduled. For the treatment discontinuation, we only considered drug discontinuation due to adverse events [51, 57].

A.1.3 Remote monitoring technology

Remote monitoring technology is not yet mature and there is no standardized performance evaluation. We used the sensitivity and specificity of the technology from Lin, et.al. [44] that compared several machine-learning-based chronic depression monitoring algorithms. We selected the sensitivity and specificity of the best-performed method [44] as our base case. In the sensitivity analysis, we first explored how the sensitivity and specificity of the technology would affect its cost-effectiveness under different monitoring costs for all three groups. We exhaustively tested all sensitivity and specificity ranging from 0 to 1 with a gap of 0.1.

A.1.4 Treatment effectiveness

While different treatments can have similar remission and response rates, existing studies have shown that treatment tends to be less effective as patients become sicker and undergo multiple treatment lines [51, 58]. In this model, we used the same remission and response probability for every three treatment lines. We estimated the remission and response probability as 0.397 and 0.631 in the base case, respectively, for the 1st treatment line and used the relative risk versus the first line to calculate the effectiveness for the remaining lines [51, 58]. In the sensitivity analysis, we changed the treatment effectiveness in three ways: adjusting only the remission and response probability in the 1st line; adjusting only the relative risk for the 2nd -9th lines; and adjusting both.

A.1.5 Costs

All costs were adjusted to 2023 USD.

Since remote monitoring is a relatively new technology, we assumed it could be a smartphone app to survey PHQ-9 combined with a call for medical consultation or follow-up scheduling. Thus, we estimated the base case monitoring cost according to CPT codes 99441 and 98966 [59] to be $10 in the Year 2019. We estimated the upper bound to be $20 based on the remote physiologic monitoring CPT code 99453 [59]. For the lower bound, we assumed free technology usage [60]. We adjusted the cost to Year 2023.

We estimated the follow-up cost to be $110 from the 2019 CPT code 99214 and estimated the lower bound and upper bound from CPT code 99213 and 99215, respectively [61] in the Year 2019. We separated the follow-up appointment cost from the total healthcare cost which is used as the background treatment cost [62]. We calculated the monthly drug cost based on commonly prescribed antidepressants such as fluoxetine and sertraline [64] and their current price [63] (see Table A.1). When a patient drops out of treatment due to an adverse event, we subtracted only the drug cost from the background treatment cost. We used the same treatment cost for treatment lines with the same remission and response probability. The background cost increased with additional treatment lines, denoting the patients' deteriorating general health conditions by failing multiple treatments [62]. We adjusted the cost to Year 2023.

Table A.1: Monthly drug cost estimation in the Year 2019

Drug	Dosage (mg/day)	# Patients	% Patients	Average monthly cost	Weighted average cost
Citalopram	20	6304	17%	16	2.72
Duloxetine	60	4460	12%	123.47	14.86
Bupropion	300	4364	12%	64.32	7.57
Sertraline	50	4173	11%	27.59	3.11
Fluoxetine	20	3631	10%	21.23	2.08
Escitalopram	20	3475	9%	71.41	6.69
Trazodone	100	3220	9%	15.4	1.34
Venlafaxine	150	2989	8%	71.54	5.77
Mirtazapine	15	2248	6%	38.29	2.32
Paroxetine	20	2201	6%	22.24	1.32
Total		37065	100%		47.78

A.1.6 Health utility

We estimated the utility values based on the PHQ-9 score range assigned for each level. In the base case, the utility for levels S, M, and H was 0.493, 0.62, and 0.7, respectively [65].

A.2 Supplement Results from One-Way Sensitivity Analysis

We varied the parameters to their lower and upper bound separately. For the treatment effects, since the remission rate and response rate for the 2nd-9th treatment lines are measured as a relative risk to the first line, we varied them in two scenarios: changing only the first line remission and response rate or keeping the first line and changing the relative risks. The first way is interpreted as improving or weakening all treatment effects, while the second way examines the impact of increasing or decreasing the difference between treatment lines. We varied the remission rate, the response rate, and the background treatment cost for each line in the same direction.

Tornado plots of the ICERs for adaptive technology versus rule-based strategy in the three groups as shown in Figures A.1 to A.3. The majority of the ICERs are below $81,630/QALY, which means the technology is robustly cost-effective. In all groups, the two most significant parameters are background treatment cost increment through treatment lines and remission/response rate for all treatment lines, followed by the utility of severe depression. The remission/response reduction through treatment lines and drug costs is also important. Thus, remote monitoring technology is more cost-effective if patients spend less for further treatment after failures, if the treatment is more effective, and if patients suffer more from severe depression.

A.3 Other Supplemental Tables and Figures

Table A.2: Three depression levels for the Markov model

Depression severity level	PHQ-9 score range
H (healthy)	0 - 4
M (mild)	5 - 9
S (moderate & severe)	10 - 27

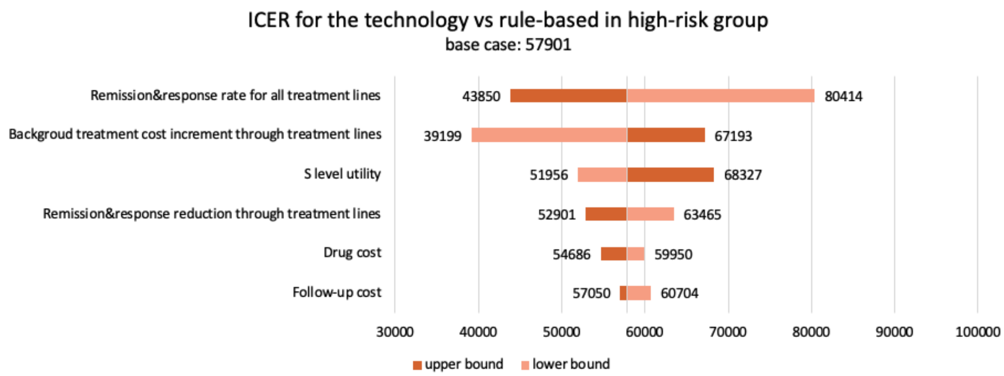


Figure A.1: Tornado plot for one-way sensitivity analysis in the high-risk group

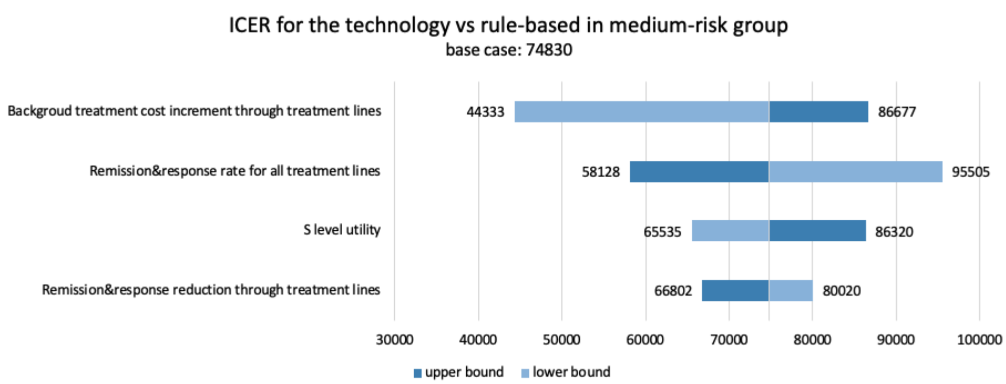


Figure A.2: Tornado plot for one-way sensitivity analysis in the medium-risk group

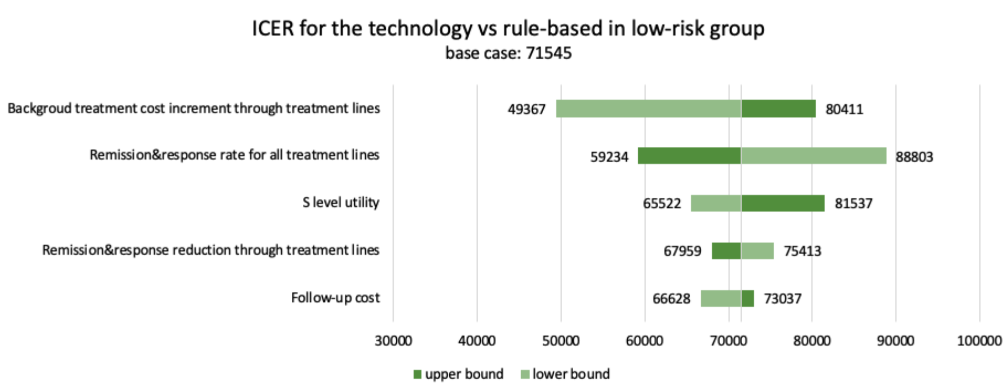


Figure A.3: Tornado plot for one-way sensitivity analysis in the low-risk group

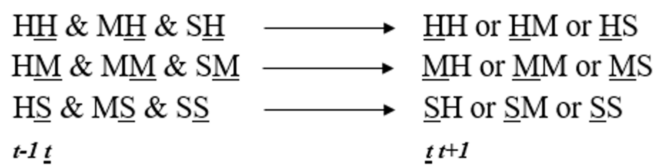


Figure A.4: All feasible Markov state transitions

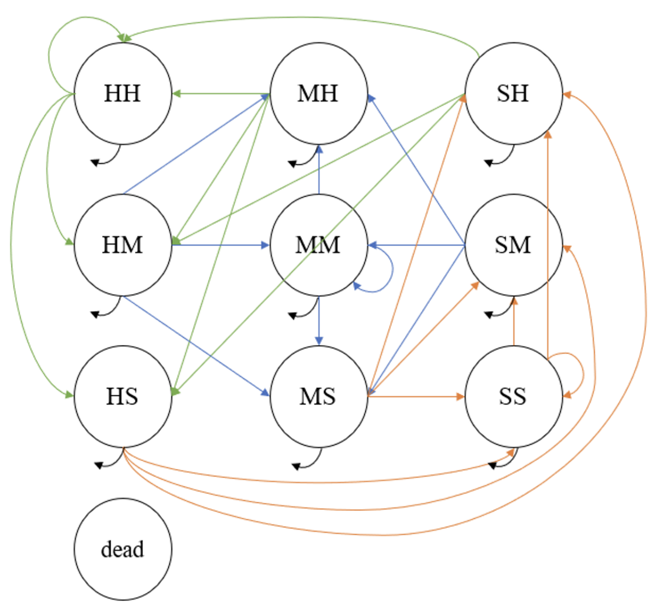


Figure A.5: Overview of the Markov-cohort model to simulate depression progression

Table A.3: Transition matrix for the high-risk group

	HH	MH	SH	HM	MM	SM	HS	MS	SS
HH	0.8333			0.1667			0.0000		
MH	0.2941			0.6471			0.0588		
SH	0.1333			0.4667			0.4000		
HM		0.0588			0.6471			0.2941	
MM		0.1343			0.7313			0.1343	
SM		0.1250			0.2625			0.6125	
HS			0.1111			0.0000			0.8889
MS			0.0625			0.1406			0.7969
SS			0.0098			0.0669			0.9233

Table A.4: Transition matrix for the medium-risk group

	HH	MH	SH	HM	MM	SM	HS	MS	SS
HH	0.7869			0.2131			0.0000		
MH	0.3582			0.4478			0.1940		
SH	0.1795			0.5641			0.2564		
HM		0.2188			0.5313			0.2500	
MM		0.0838			0.7614			0.1548	
SM		0.1394			0.3990			0.4615	
HS			0.1111			0.2963			0.5926
MS			0.0538			0.2097			0.7366
SS			0.0244			0.1388			0.8368

Table A.5: Transition matrix for the low-risk group

	HH	MH	SH	HM	MM	SM	HS	MS	SS
HH	0.8762			0.1158			0.0080		
MH	0.5321			0.4312			0.0367		
SH	0.3226			0.4194			0.2581		
HM		0.2602			0.6098			0.1301	
MM		0.1730			0.7075			0.1195	
SM		0.2881			0.5254			0.1864	
HS			0.2500			0.1875			0.5625
MS			0.0968			0.2258			0.6774
SS			0.0414			0.1862			0.7724

Table A.6: Initial distribution for the high-risk group

HH	MH	SH	HM	MM	SM	HS	MS	SS
0	0	0	0	0	0	0.0234	0.0469	0.9297

Table A.7: Initial distribution for the medium-risk group

HH	MH	SH	HM	MM	SM	HS	MS	SS
0	0	0	0.0260	0.1250	0.1302	0.0313	0.1198	0.5677

Table A.8: Initial distribution for the low-risk group

HH	MH	SH	HM	MM	SM	HS	MS	SS
0.3306	0.0968	0.1452	0.0645	0.2177	0.1452	0	0	0

Table A.9: Base case results for the high-risk group

Strategy	Cost, $	QALYs	ICER, $/QALY
Fixed frequency 6-month	36569	1.0545	
Fixed frequency 4-month	37620	1.0752	50734
Rule-based	39328	1.1049	57570
Remote monitoring technology	39757	1.1123	57901
Fixed frequency 2-month	39825	1.1127	173366

Table A.10: Base case results for the medium-risk group

Strategy	Cost, $	QALYs	ICER, $/QALY	
Fixed frequency 6-month	36487	1.1020		
Fixed frequency 4-month	37515	1.1172	67702	
Rule-based	38964	1.1363	75707	extended dominated
Remote monitoring technology	39662	1.1459	74830	
Fixed frequency 2-month	39750	1.1452	-127741	dominated

Table A.11: Base case results for the low-risk group

Strategy	Cost, $	QALYs	ICER, $/QALY	
Fixed frequency 6-month	36240	1.2314		
Fixed frequency 4-month	36898	1.2410	68488	
Rule-based	37385	1.2479	71223	
Remote monitoring technology	38331	1.2611	71545	
Fixed frequency 2-month	38642	1.2600	-283740	dominated

Table A.12: Parameter settings in sensitivity analysis of technology factors

Factor	Number of levels	Levels
Sensitivity of the technology	11	[0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
Specificity of the technology	11	[0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
Cost of the technology, per month	3	[$0, $10, $20]
Group type	3	[High-risk, Medium-risk, Low-risk]

Table A.13: Scenarios for two-way and multi-way sensitivity analysis

No.	Scenarios
1	low follow-up discontinuation; low treatment discontinuation
2	high follow-up discontinuation; high treatment discontinuation

3	low all-line remission&response probability
4	high all-line remission&response probability
5	low all-line remission&response probability; low treatment discontinuation
6	high all-line remission&response probability; high treatment discontinuation
7	low all-line remission&response probability; high treatment discontinuation
8	high all-line remission&response probability; low treatment discontinuation
9	low all-line remission&response probability; low drug cost
10	high all-line remission&response probability; high drug cost
11	low all-line remission&response probability; high drug cost
12	high all-line remission&response probability; low drug cost
13	low 1st-3rd line remission&response probability; low treatment discontinuation
14	high 1st-3rd line remission&response probability; high treatment discontinuation
15	low 1st-3rd line remission&response probability; high treatment discontinuation
16	high 1st-3rd line remission&response probability; low treatment discontinuation
17	low 1st-3rd line remission&response probability; low drug cost
18	high 1st-3rd line remission&response probability; high drug cost
19	low 1st-3rd line remission&response probability; high drug cost
20	high 1st-3rd line remission&response probability; low drug cost
21	low 4th-9th line remission&response relative risk; low treatment discontinuation
22	high 4th-9th line remission&response relative risk; high treatment discontinuation
23	low 4th-9th line remission&response relative risk; high treatment discontinuation
24	high 4th-9th line remission&response relative risk; low treatment discontinuation
25	low background treatment cost; low follow-up cost
26	high background treatment cost; high follow-up cost
27	low background treatment cost; high follow-up cost
28	high background treatment cost; low follow-up cost
29	low background treatment cost; low drug cost

30	high background treatment cost; high drug cost
31	low background treatment cost; high drug cost
32	high background treatment cost; low drug cost
33	low follow-up cost; low drug cost
34	high follow-up cost; high drug cost
35	low follow-up cost; high drug cost
36	high follow-up cost; low drug cost
37	low 4th-9th line remission&response relative risk; low drug cost
38	high 4th-9th line remission&response relative risk; high drug cost
39	low 4th-9th line remission&response relative risk; high drug cost
40	high 4th-9th line remission&response relative risk; low drug cost
41	low background treatment cost; low follow-up cost; low drug cost
42	high background treatment cost; high follow-up cost; high drug cost
43	low background treatment cost; low follow-up cost; high drug cost
44	high background treatment cost; high follow-up cost; low drug cost
45	low background treatment cost; high follow-up cost; high drug cost
46	high background treatment cost; low follow-up cost; low drug cost
47	low utility; high follow-up discontinuation; high mortality hazard ratio
48	high utility; low follow-up discontinuation; low mortality hazard ratio

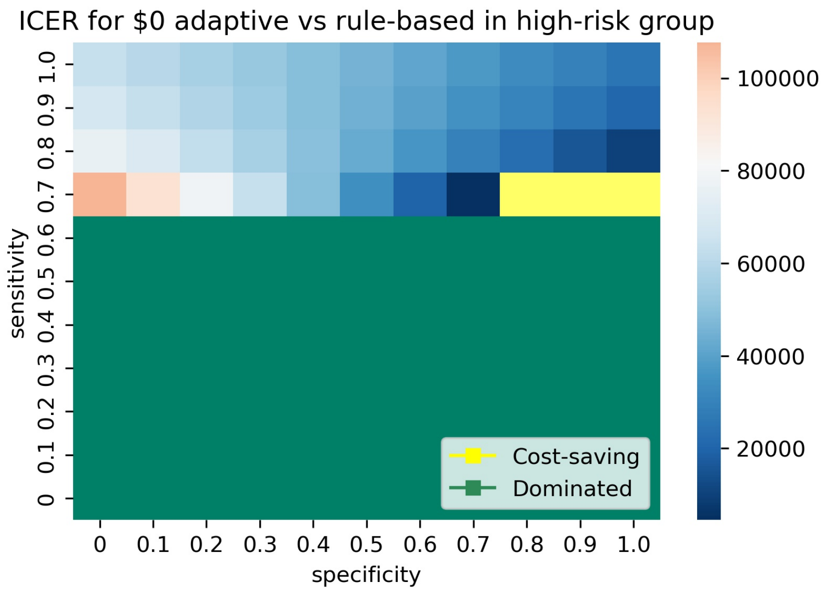


Figure A.6: ICER for $0 adaptive remote monitoring technology versus rule-based follow-up strategy in the high-risk group

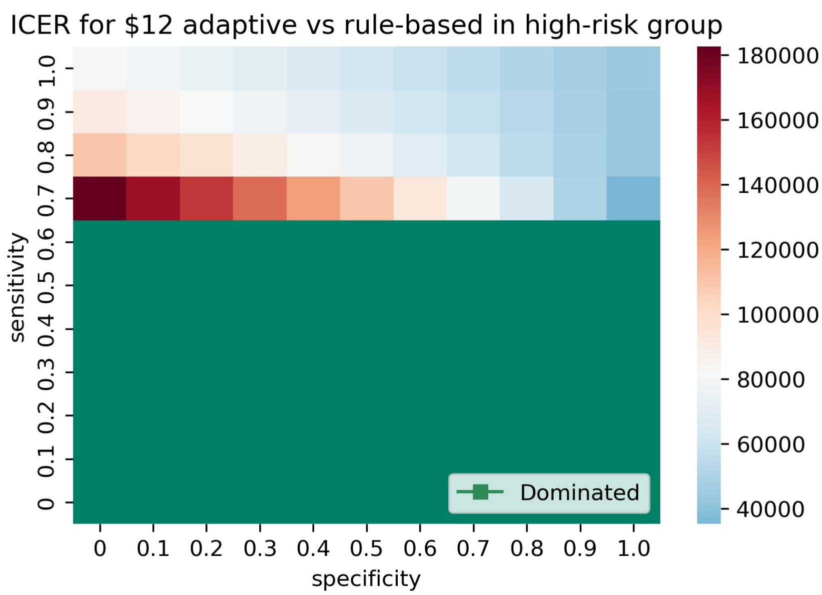


Figure A.7: ICER for $12 adaptive remote monitoring technology versus rule-based follow-up strategy in the high-risk group

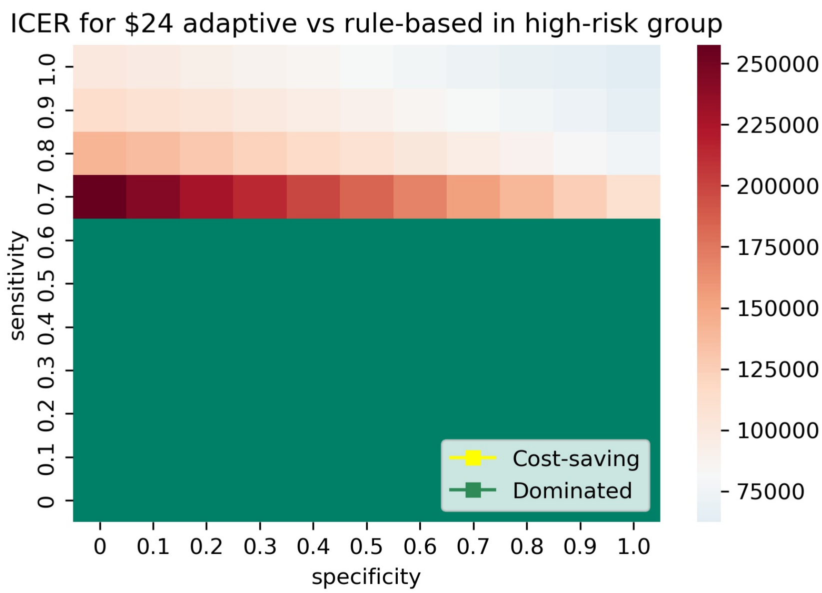


Figure A.8: ICER for $24 adaptive remote monitoring technology versus rule-based follow-up strategy in the high-risk group

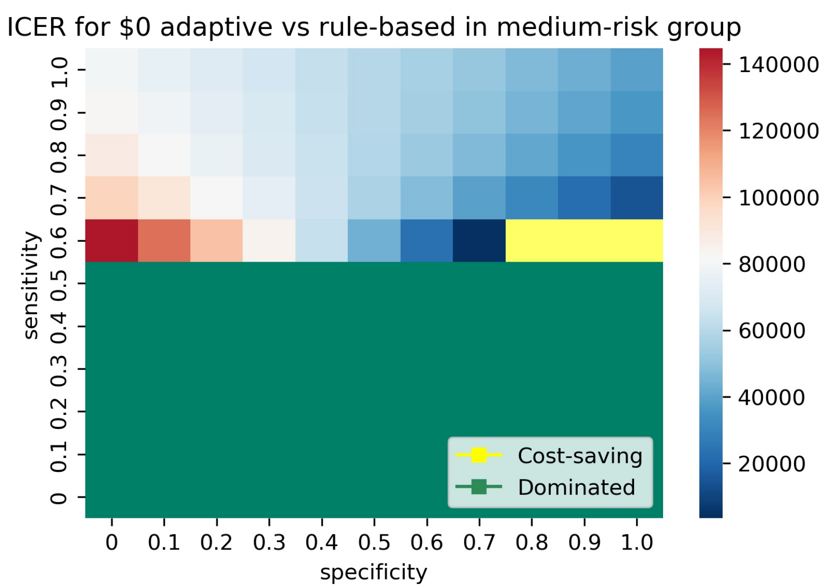


Figure A.9: ICER for $0 adaptive remote monitoring technology versus rule-based follow-up strategy in the medium-risk group

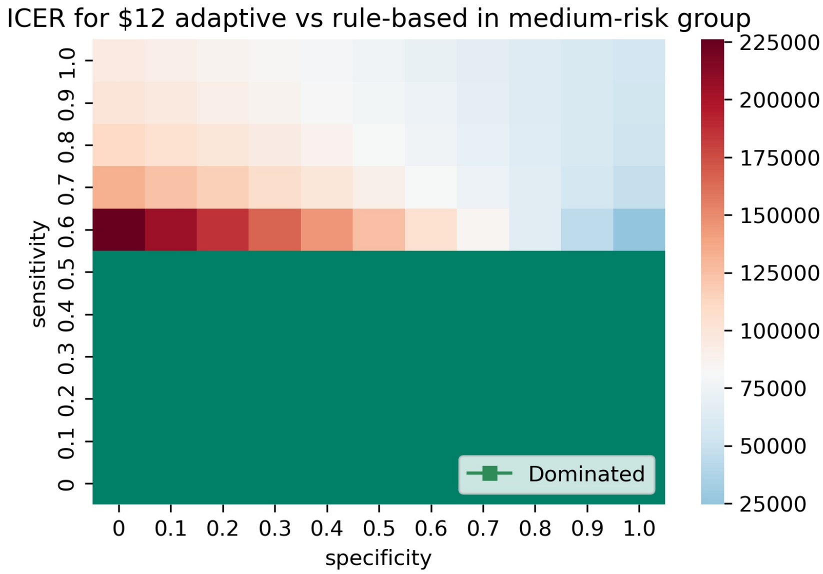


Figure A.10: ICER for $12 adaptive remote monitoring technology versus rule-based follow-up strategy in the medium-risk group

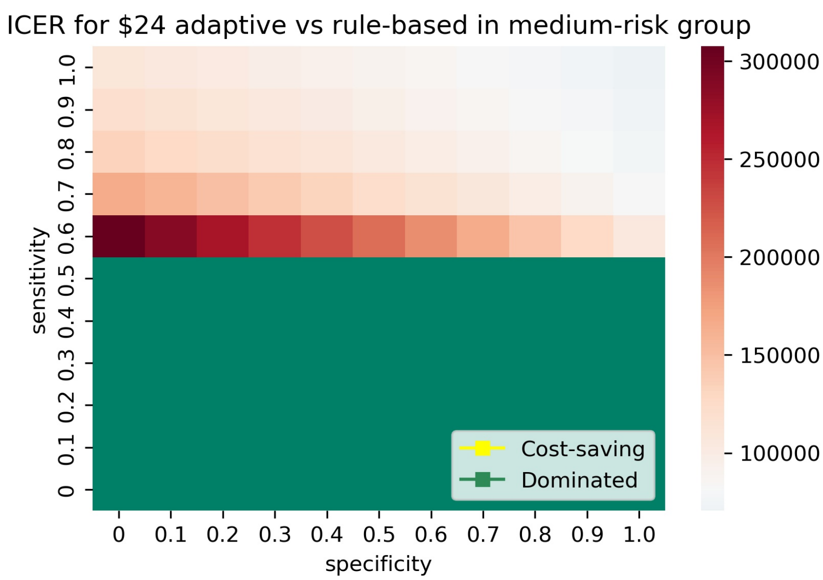


Figure A.11: ICER for $24 adaptive remote monitoring technology versus rule-based follow-up strategy in the medium-risk group

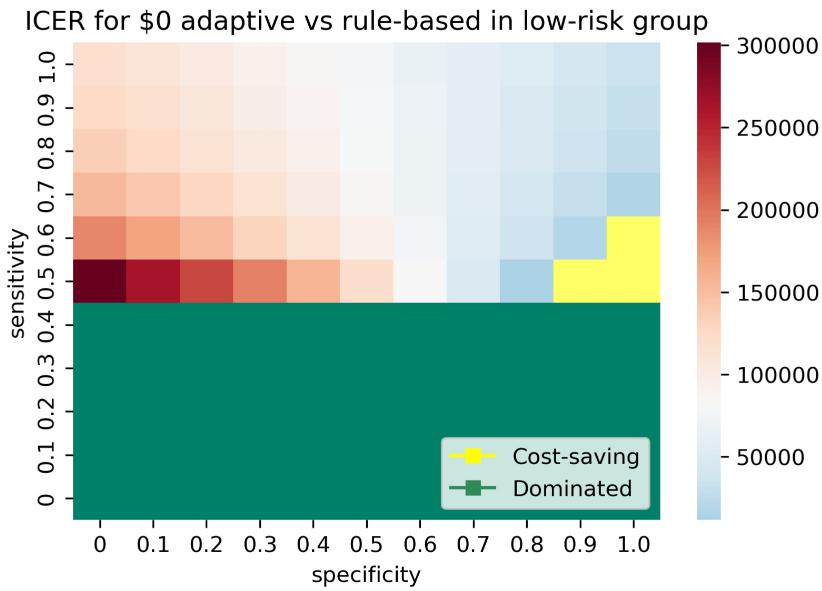


Figure A.12: ICER for $0 adaptive remote monitoring technology versus rule-based follow-up strategy in the low-risk group

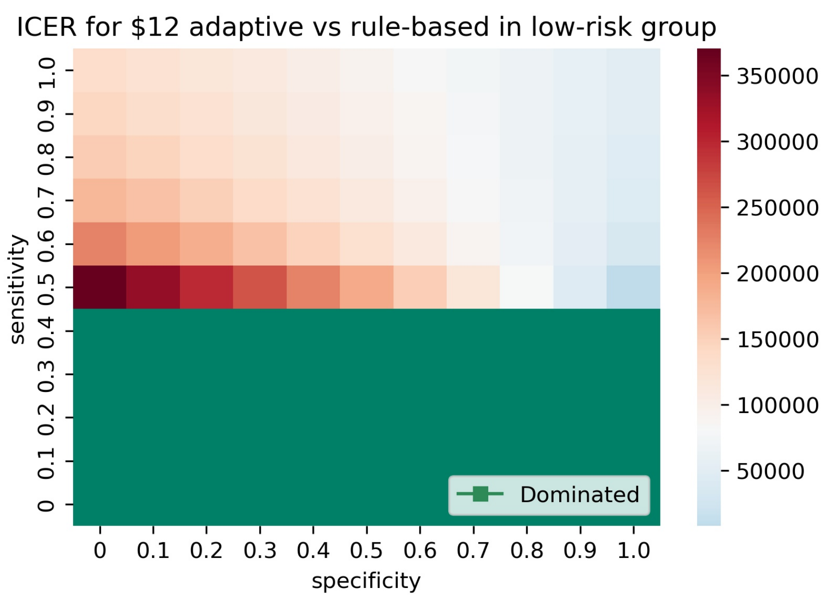


Figure A.13: ICER for $12 adaptive remote monitoring technology versus rule-based follow-up strategy in the low-risk group

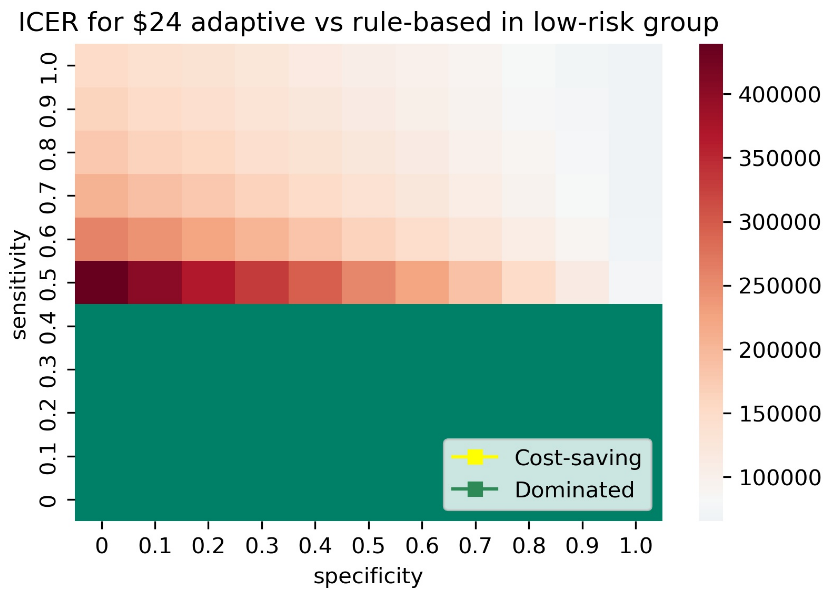


Figure A.14: ICER for $24 adaptive remote monitoring technology versus rule-based follow-up strategy in the low-risk group

Appendix B

APPENDIX OF CHAPTER 3

B.1 Supplemental Methods

B.1.1 PCG supplement

Using our team's trauma expertise, we grouped specific MPs into larger groups of common procedures performed for injuries (i.e., craniotomy, repair of open fracture of the upper extremity, etc.) (Table B.1), then linked these categories to the related body region and the AIS score for that body region. The body regions include the head, neck, face, upper extremities, lower extremities, chest, and abdomen. We obtained the maximum AIS score from the ISS calculation R package [95] for each of the six ISS body regions: head and neck, face, extremities, chest, abdomen, and general. For the diagnosis codes that are not successfully converted, we matched them with AIS codes provided by the coder in Harborview Medical Center, then identified the injury body regions and injury scores. The 1st digit of the AIS code represents body region, which includes head, face, neck, thorax, abdomen, spine, upper extremity, lower extremity, and unspecified; the 7th digit of the AIS code represents severity score, which includes 1,2,3,4,5,6, and 9 [94]. Since the AIS code is in more detail than the ICD-10-CM code, each diagnosis code may be related to more than one AIS code. To match what we obtained from the ISS calculation R package [95], we converted the AIS code body region as shown in Table B.2. If one diagnosis code is related to more than one severity score, we calculated the average to be the injury score of that code; If the score is 9 which is not further specified, we treated it as 0. Then we calculated the maximum AIS score for each of the six ISS body regions for admissions with unconverted diagnosis code(s). Since we do not know which diagnosis related to which procedure, we assigned the augmented body region maximum AIS scores accordingly to the PCGs as shown in Table B.3

within the same admission to approximate the injury severity for each procedure.

Table B.1: Common procedure categories for PCGs

Category No.	Common procedure categories
1	Amputation
2	Cardiac
3	Control of hemorrhage
4	Craniectomy
5	Craniotomy
6	Ex fix
7	Exploratory laparotomy/other abdominal surgery
8	Facial fractures
9	Gynecology
10	Joint
11	Neck exploration
12	Open fixation
13	Open pelvis fixation
14	Ophthalmology
15	Other ent
16	Other general surgery
17	Other neurosurgery
18	Other orthopedics
19	Other subspecialty
20	Other thoracic
21	Other urology
22	Other vascular procedures

23	Pelvis external fixation
24	Percutaneous fixation
25	Percutaneous pelvic fixation
26	Peripheral nerve
27	Reconstruction
28	Rib fixation
29	Spine procedures

Table B.2: AIS conversion

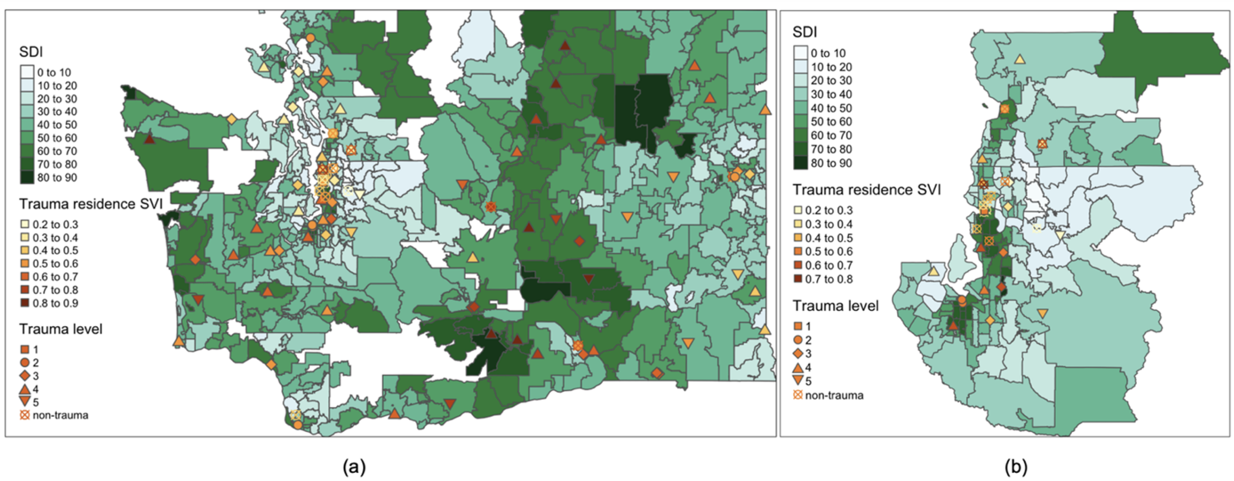
1st digit of the AIS code	AIS code body region	Conversion method
1	Head	Belongs to ”head and neck”
2	Face	Belongs to ”face”
3	Neck	Belongs to ”head and neck”
4	Thorax	Belongs to ”chest”
5	Abdomen	Belongs to ”abdomen”
6	Spine	Manually checked each related diagnosis code and grouped
7	Upper extremity	Belongs to ”extremities”
8	Lower extremity	Belongs to ”extremities”
9	Unspecified	Belongs to ”general”

Table B.3: PCG body region AIS severity score assignment

PCG body region	Assigned AIS score
Head	Maximum "head and neck" AIS score
Neck	Maximum "head and neck" AIS score
Face	Maximum "face" AIS score
Upper extremities	Maximum "extremities" AIS score
Lower extremities	Maximum "extremities" AIS score
Chest	Maximum "chest" AIS score
Abdomen	Maximum "abdomen" AIS score

B.1.2 Social indices supplement

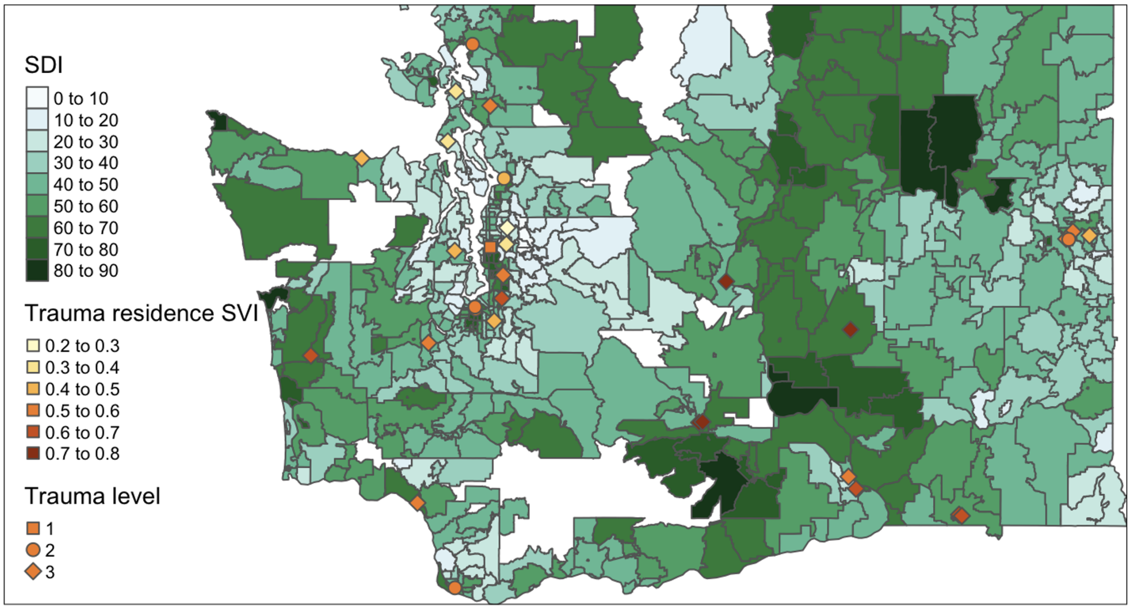
We used the Social Vulnerability Index (SVI) [101] for patients' home residences and Social Deprivation Index (SDI) [102] for hospitals' locations. Social vulnerability is derived using several factors including poverty, lack of access to transportation, and crowded housing that may weaken a community's ability to prevent human suffering and financial loss in a disaster [101]. The SVI ranks each census tract on these social factors based on percentiles with values ranging from 0 to 1, with higher values indicating greater vulnerability [101]. The SDI was developed to quantify levels of disadvantage in income, education, housing, transportation, and employment across small areas, evaluate their associations with health outcomes, and address health inequities [102]. The SDI ranges from 0 to 100 for each census tract with higher scores indicating higher deprivation [102]. We linked the zip codes of the patient residences and hospital addresses to census tracts [216], then averaged the SVI and SDI across the census tracts in each zip code. We included social indices to explore the relationship between the SDI of TCs/non-TCs location and SVI of the patient residence and we expect that patients living in areas with higher SVI tend to go to TCs/non-TCs located in the area with higher SDI. We calculated the patient SVI for each hospital as the average SVI among all the patient residence zip codes. Figure B.1 maps the SDI of hospital zip codes with average patient SVI in TCs/non-TCs in WA state and zooms in on King County, Snohomish County, and Pierce County. Figure B.2 includes only level I, II, and III TCs instead of all level TCs/non-TCs in WA state.



Each symbol represents a TC/non-TC.

Average patient SVI: calculated as the average SVI among all the patient residence zip codes for each TC/non-TC.

Figure B.1: (a) SDI of hospital zip code with average patient SVI in TCs/non-TCs in WA state, (b) SDI of hospital zip code with average patient SVI in TCs/non-TCs in King County, Snohomish County, and Pierce County



Each symbol represents a TC/non-TC.

Average patient SVI: calculated as the average SVI among all the patient residence zip codes for each TC/non-TC.

Figure B.2: SDI of hospital zip code with average patient SVI in level I, II, III TCs in WA state

B.1.3 Clustering analysis method supplement

For Set 1 and Set 2, we standardized the original features to be on the same scale. Specifically, we standardized the features that are not in the [0, 1] range to [0, 1] using the min-max standardization [217]:

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{B.1}$$

, where $\min(x)/\max(x)$ is the minimum/maximum value of this feature among all hospitals. For SDI with a range of [0, 100], we divided it by 100 to scale it down to the [0, 1] range. For Set 3-1 and Set 3-2, the features are already on the same scale, therefore, no standardization is needed. For each set, we carried out Principal Component Analysis (PCA) on the standardized features to reduce the dimensions of the original features and remove collinearity.

PCA is an orthogonal linear transformation of the original features into new independent features denoted as principal components [103]. The 1st principal component is the most important since it contains the most variation in the data, the 2nd principal component contains the second most variation, and so on [103]. We selected the top components reaching 90% of the total variation [103]. We conducted an unsupervised clustering analysis using Partition Around Medoids (PAM) [104] method on WA TCs/non-TCs based on the selected principal components. We chose the number of clusters mainly based on the Silhouette method, which is a measure of how similar a TC/non-TC is to its own cluster compared to other clusters [218]. We displayed the results using t-distributed stochastic neighbor embedding (t-SNE) [219], which is a statistical method for visualizing high-dimensional data by giving each data point a location in a two or three-dimensional map.

B.1.4 Other supplemental tables

Table B.4: Transfer-out status list

Code	Code value
1	Discharged to home/self care (routine charge).
2	Discharged/transferred to other short term general hospital for inpatient care.
3	Discharged/transferred to skilled nursing facility (SNF) with Medicare certification in anticipation of covered skilled care – (For hospitals with an approved swing bed arrangement, use Code 61 - swing bed. For reporting discharges/transfers to a non-certified SNF, the hospital must use Code 04 - ICF.
4	Discharged/transferred to intermediate care facility (ICF).
5	Discharged/transferred to another type of institution for inpatient care (including distinct parts). NOTE: Effective 1/2005, psychiatric hospital or psychiatric distinct part unit of a hospital will no longer be identified by this code. New code is '65'
6	Discharged/transferred to home care of organized home health service organization.
7	Left against medical advice or discontinued care.

8 Discharged/transferred to home under care of a home IV drug therapy provider. (discontinued effective 10/1/05)

9 Admitted as an inpatient to this hospital (effective 3/1/91). In situations where a patient is admitted before midnight of the third day following the day of an outpatient service, the outpatient services are considered inpatient.

20 Expired (did not recover - Christian Science patient).

21 Discharged/transferred to Court/Law Enforcement (eff. 10/2009)

30 Still patient or expected to return for outpatient services

40 Expired at home (hospice claims only)

41 Expired in a medical facility such as hospital, SNF, ICF, or freestanding hospice. (Hospice claims only)

42 Expired - place unknown (Hospice claims only)

43 Discharged/transferred to a federal hospital (eff. 10/1/03)

50 Hospice - home (eff. 10/96)

51 Hospice - medical facility (eff. 10/96)

61 Discharged/transferred within this institution to a hospital-based Medicare approved swing bed (eff. 9/01)

62 Discharged/transferred to an inpatient rehabilitation facility including distinct parts units of a hospital. (eff. 1/2002)

63 Discharged/transferred to a long term care hospitals. (eff. 1/2002)

65 Discharged/Transferred to a psychiatric hospital or psychiatric distinct unit of a hospital (these types of hospitals were pulled from patient/discharge status code '05' and given their own code). (eff. 1/2005).

66 Discharged/transferred to a Critical Access Hospital (CAH) (eff. 1/1/06)

69 Discharged/transferred to a designated disaster alternative care site (eff. 10/2013)

70 Discharged/transferred to another type of health care institution not defined elsewhere in code list.

71 Discharged/transferred/referred to another institution for outpatient services as specified by the discharge plan of care (eff. 9/01) (discontinued effective 10/1/05)

81 Discharged to home or self-care with a planned acute care hospital readmission (eff. 10/2013)

82 Discharged/transferred to a short term general hospital for inpatient care with a planned acute care hospital inpatient readmission (eff. 10/2013)

83 Discharged/transferred to a skilled nursing facility (SNF) with Medicare certification with a planned acute care hospital inpatient readmission (eff. 10/2013)

84 Discharged/transferred to a facility that provides custodial or supportive care with a planned acute care hospital inpatient readmission (eff. 10/2013)

85 Discharged/transferred to a designated cancer center or children's hospital with a planned acute care hospital inpatient readmission (eff. 10/2013)

86 Discharged/transferred to home under care of organized home health service organization with a planned acute care hospital inpatient readmission (eff. 10/2013)

87 Discharged/transferred to court/law enforcement with a planned acute care hospital inpatient readmission (eff. 10/2013)

88 Discharged/transferred to a federal health care facility with a planned acute care hospital inpatient readmission (eff. 10/2013)

89 Discharged/transferred to a hospital-based Medicare approved swing bed with a planned acute care hospital inpatient readmission (eff. 10/2013)

90 Discharged/transferred to an inpatient rehabilitation facility (IRF) including rehabilitation distinct part units of a hospital with a planned acute care hospital inpatient readmission (eff. 10/2013)

91 Discharged/transferred to a Medicare certified long term care hospital (LTCH) with a planned acute care hospital inpatient readmission (eff. 10/2103)

92 Discharged/transferred to nursing facility certified under Medicaid but not certified under Medicare with a planned acute care hospital inpatient readmission (eff. 10/2013)

93 Discharged/transferred to a psychiatric hospital/distinct part unit of a hospital with a planned acute care hospital inpatient readmission (eff. 10/2013)

94	Discharged/transferred to a critical access hospital (CAH) with a planned acute care hospital inpatient readmission (eff. 10/2013)
95	Discharged/transferred to another type of health care institution not defined elsewhere in this code list with a planned acute care hospital inpatient readmission (eff. 10/2013)

Table B.5: Trauma diagnosis codes that cannot be converted

No.	ICD10CM Code
1	S62024B
2	S63435A
3	S82245C
4	S90529A
5	S95292A
6	T22641A
7	T22649A

Table B.6: Clustering features of set 1 and set 2

Feature category	Feature description	# Features
Gender	% Male in trauma admissions	1
	% Male in non-trauma admissions	1
Age	Age median in trauma admissions	1
	Age median in non-trauma admissions	1

Admission type	# Trauma admission	1
	% Trauma admission in total admissions	1
Transfer type	% Transferred-in in trauma admissions	1
	% Transferred-out in trauma admissions	1
	% Transferred-in in non-trauma admissions	1
	% Transferred-out in non-trauma admissions	1
Insurance payer type	% Private payer in trauma admissions	1
	% Private payer in non-trauma admissions	1
	% low-income payer in trauma admissions	1
	% low-income payer in non-trauma admissions	1
ISS	Min ISS median in trauma admissions	1
	% Min ISS over 15 in trauma admissions (/ # of min ISS exists)	1
Mechanism type	% Blunt in trauma admissions	1
	% Penetrating in trauma admissions	1
	% Burn in trauma admissions	1
Social Index	SDI in the TC/non-TC area	1
	SVI mean in trauma admissions' residence	1
	SVI mean in non-trauma admissions' residence	1
MPs	# MPs carried out for non-trauma admissions	1
	# MPs carried out for trauma admissions	1
	% All the 6 subgroups in total MPs for non-trauma admissions	6
	% All the 6 subgroups in total MPs for trauma admissions	6
PCG	Cluster labels of # PCG in Major General Surgery for trauma admissions	1
	Cluster labels of # PCG in Major Orthopedics for trauma admissions	1
	Cluster labels of # PCG in Major Neurosurgery for trauma admissions	1
	Cluster labels of # PCG in Major Urology for trauma admissions	1

	Cluster labels of # PCG in Major Subspecialty for trauma admissions	1
PCG	% Each PCG in MPs for trauma admissions	438

Abbreviations: ISS (Injury Severity Score); SDI (Social Deprivation Index); SVI (Social Vulnerability Index); MP (major therapeutic procedures); PCG (Procedure Complexity Group).

B.2 *Supplemental Results*

Table B.7: Summary of surgical care and other features by trauma center level for all state hospitals (TCs and non-TCs)

	Trauma center level							
TC/non-TC features	**Total**	**I**	**II**	**III**	**IV**	**V**	**Non-Trauma**	**P-value**†
Number of hospitals	100	1	7	24	35	14	19	/
Admission type								
Total admissions, n	635973	14747	152800	242018	85695	4562	136151	/
Total trauma admission, n (%)	34645 (5%)	5605 (38%)	9011 (6%)	11364 (5%)	4277 (5%)	240 (5%)	4148 (3%)	< 0.001
Trauma Admissions, per hospital, med (IQR)	102.5 (13.75, 424.75)	5605	1305 (1066, 1632)	425 (237.5, 647.2)	66 (19, 137.5)	9 (2, 15.25)	17 (3.5, 338.5)	< 0.001
Gender								
Admissions Female, n (%)	362747 (57%)	5295 (36%)	86058 (56%)	142417 (59%)	49285 (58%)	2827 (62%)	76865 (56%)	< 0.001
Trauma admissions female, n (%)	17168 (50%)	1758 (31%)	4253 (47%)	6143 (54%)	2520 (59%)	153 (64%)	2341 (56%)	< 0.001

Female trauma patients, by hospital, med (IQR)	62 (9, 242)	1758	594 (509.5, 800.5)	240.5 (117, 353.8)	42 (9, 76.5)	8 (5, 10.5)	4 (2, 186.5)	< 0.001
Age								
Age in years- all patients, med (IQR)	53 (27, 70)	53 (36, 65)	53 (25, 70)	54 (27, 72)	59 (32, 74)	55 (25, 75)	46 (22, 67)	0.005
Age in years- trauma patients, med (IQR)	66 (46, 81)	47 (28, 64)	63 (41, 78)	71 (56, 84)	73 (58, 85)	75 (62, 86)	69 (49, 83)	< 0.001[‡]
Transfer type								
Trauma admit transferred in, n (%)	4897 (14%)	2832 (51%)	734 (8%)	485 (4%)	86 (2%)	0 (0%)	760 (18%)	< 0.001
Trauma admissions transferred in, per hospital, med (IQR)	1 (0, 11)[§]	2832	65 (40, 110.5)	7.5 (1, 23.75)	1 (0, 2.5)	0 (0, 0)	3 (1, 47)	< 0.001
Patients transfer out total, n (% in admission)	15128 (2%)	204 (1%)	1752 (1%)	5447 (2%)	4426 (5%)	492 (11%)	2807 (2%)	< 0.001
Trauma patients transferred out, n (%)[¶]	996 (3%)	80 (1%)	183 (2%)	313 (3%)	261 (6%)	49 (20%)	110 (3%)	< 0.001
Trauma patients transferred out, per hospital [‖], med (IQR)	6 (2, 12.25)	80	18 (15.5, 31.5)	12 (8.75, 15.75)	6 (4, 9.5)	2 (0, 5.75)	1 (0, 6.5)	< 0.001
Payer type in trauma admissions[††]								
Private, n (%)	10286 (30%)	2243 (40%)	2829 (31%)	2975 (26%)	1122 (26%)	49 (20%)	1068 (26%)	< 0.001
Low Income, n (%)	6394 (18%)	1882 (34%)	1975 (22%)	1303 (11%)	576 (13%)	27 (11%)	631 (15%)	

Other, n (%)††	17965 (52%)	1480 (26%)	4207 (47%)	7086 (62%)	2579 (60%)	164 (68%)	2449 (59%)	
Percent private per hospital, med % (IQR)	23% (11%, 29%)	0.4	31% (29%, 35%)	23% (17%, 26%)	18% (9%, 28%)	8% (3%, 23%)	24% (22%, 33%)	0.01
Percent low-income per hospital, med % (IQR)	13% (6%, 19%)	0.34	20% (17%, 27%)	12% (9%, 14%)	11% (3%, 17%)	11% (3%, 16%)	12% (2%, 42%)	0.09
Percent other per hospital, med % (IQR)	65% (52%, 75%)	0.26	52% (36%, 53%)	64% (58%, 69%)	70% (55%, 84%)	80% (62%, 88%)	64% (11%, 71%)	0.007
Injury Severity Score (ISS)								
ISS§, med (IQR)	4 (1, 10)	9 (2, 19)	6 (1, 16)	4 (1, 9)	4 (1, 9)	4 (1, 9)	4 (1, 9)	0.007‡‡
Injury Mechanism in trauma admissions								
Total Blunt, n (%)	25384 (73%)	3837 (68%)	6761 (75%)	8676 (76%)	3151 (74%)	151 (63%)	2808 (68%)	
Total Penetrating, n (%)	1503 (4%)	435 (8%)	470 (5%)	341 (3%)	149 (3%)	***	107 (3%)	< 0.001
Total Burn, n (%)	540 (2%)	411 (7%)	48 (1%)	51 (0.4%)	13 (0.3%)	***	13 (0.3%)	
Total Other, n (%)	3247 (9%)	372 (7%)	914 (10%)	1125 (10%)	429 (10%)	14 (6%)	393 (9%)	
Total Missing, n (%)	3971 (11%)	550 (10%)	818 (9%)	1171 (10%)	535 (13%)	70 (29%)	827 (20%)	
Blunt per hospital, med (IQR)	82 (8, 314)	3837	973 (779, 1257.5)	334.5 (182.2, 500.5)	51 (14.5, 101)	5 (4, 13)	1 (0, 219.5)	< 0.001

Penetrating per hospital, med (IQR)	3 (0, 13)	435	71 (46, 90)	12.5 (8, 19.25)	2 (0, 5.5)	0 (0, 0)	0 (0, 5.5)	< 0.001
Burn per hospital, med (IQR)	0 (0, 2)	411	7 (5.5, 7)	2 (1, 3.25)	0 (0, 0.5)	0 (0, 1)	0 (0, 1)	< 0.001
Other per hospital, med (IQR)	7 (0, 44)	372	140 (103, 172)	43 (18.75, 55.25)	3 (1, 11.5)	0 (0, 0)	0 (0, 28)	< 0.001
Social Index								
SDI in hospital area, by hospital, med (IQR)	54 (45.6, 65.83)	73.88	75 (68.73, 91.5)	54.06 (44.73, 69.01)	53.67 (48.31, 61.08)	46.4 (42.33, 53.38)	49.67 (40.72, 66.11)	0.01
SVI in trauma admissions' residence, med (IQR)	0.51 (0.36, 0.65)	0.51 (0.35, 0.66)	0.52 (0.41, 0.65)	0.51 (0.36, 0.65)	0.53 (0.40, 0.67)	0.44 (0.41, 0.70)	0.40 (0.18, 0.57)	< 0.001
SVI in non-trauma admissions' residence, med (IQR)	0.52 (0.36, 0.66)	0.56 (0.40, 0.68)	0.52 (0.42, 0.65)	0.52 (0.37, 0.69)	0.55 (0.43, 0.69)	0.50 (0.41, 0.78)	0.44 (0.25, 0.63)	< 0.001
Major Therapeutic Procedure (MP)								
Total MP, n	322878	16755	77357	108322	33534	1026	85884	/
Unique MP for trauma, n	3420	1688	1578	1474	694	41	1036	/
MP for trauma, n (% in total MP)	28418 (9%)	8025 (48%)	6645 (9%)	7965 (7%)	2578 (8%)	79 (8%)	3126 (4%)	< 0.001
MP for trauma by hospital, med (IQR)	198 (65, 436)	8025	911 (708, 1040)	276.5 (139.8, 451.5)	67.5 (13.75, 147.25)	39.5 (36.25, 42.75)	292 (198, 432)	< 0.001

General Surgery for trauma, n (% in MP for trauma)	3122 (11%)	1042 (13%)	934 (14%)	642 (8%)	114 (4%)	0 (0%)	390 (12%)	< 0.001
Orthopedics for trauma, n (% in MP for trauma)	19016 (67%)	4291 (53%)	4286 (64%)	6218 (78%)	2185 (85%)	75 (95%)	1961 (63%)	
Neurosurgery for trauma, n (% in MP for trauma)	3686 (13%)	1436 (18%)	840 (13%)	711 (9%)	122 (5%)	2 (3%)	575 (18%)	
Urology for trauma, n (% in MP for trauma)	187 (1%)	43 (1%)	35 (1%)	57 (1%)	19 (1%)	0 (0%)	33 (1%)	
Subspecialty for trauma, n (% in MP for trauma)	2246 (8%)	1203 (15%)	511 (8%)	279 (4%)	111 (4%)	2 (3%)	140 (4%)	
Other MP for trauma, n (% in MP for trauma)	167 (1%)	10 (0.1%)	42 (1%)	62 (1%)	30 (1%)	0 (0%)	23 (1%)	
General Surgery for non-trauma, n (% in MP for non-trauma)	108070 (37%)	2025 (23%)	31943 (45%)	33737 (34%)	8860 (29%)	164 (17%)	31341 (38%)	< 0.001
Orthopedics for non-trauma, n (% in MP for non-trauma)	58887 (20%)	2048 (23%)	11783 (17%)	20860 (21%)	9320 (30%)	263 (28%)	14613 (18%)	
Neurosurgery for non-trauma, n (% in MP for non-trauma)	40083 (14%)	3274 (38%)	7819 (11%)	13234 (13%)	3947 (13%)	7 (1%)	11802 (14%)	
Urology for non-trauma, n (% in MP for non-trauma)	13206 (4%)	273 (3%)	2768 (4%)	4060 (4%)	1296 (4%)	48 (5%)	4761 (6%)	

Subspecialty for non-trauma, n (% in MP for non-trauma)	12365 (4%)	968 (11%)	2521 (4%)	2374 (2%)	824 (3%)	11 (1%)	5667 (7%)
Other MP for non-trauma, n (% in MP for non-trauma)	61767 (21%)	98 (1%)	14015 (20%)	26149 (26%)	6697 (22%)	451 (48%)	14357 (17%)

† Statistical tests were applied based on the distribution of the data point. Obtain p-values for medians from Krusal-Wallis test, and for proportions from Chi-squared test.

‡ P-value 0.2724 for level 1 and 2; < 0.001 for level 3, 4, 5, and non-trauma.

§ Mean transfers in 46, skewed data.

¶ Does not include patients who transferred from the emergency department without hospital admission.

‖ Trauma patients only, minimum value, as some diagnostic codes did not convert.

†† Payer type: private (health maintenance organization, commercial insurance, labor and industries, or health care service contractor), low-income payer (Medicaid, self-pay, or charity care) or other payer which includes Medicare.

‡‡ P-value 0.3491 for level 1 and 2; 0.1457 for level 3, 4, 5, and non-trauma.

*** Categories with < 10 admissions in the raw count are not reported per the data use agreement.

Table B.8: Subgroup clustering for set 1

Cluster labels of	# Features	Optimal cluster number in [3, 10] by the Silhouette method
# PCG in Major General Surgery for trauma admissions	128	3
# PCG in Major Orthopedics for trauma admissions	139	3
# PCG in Major Neurosurgery for trauma admissions	77	3

# PCG in Major Urology for trauma admissions	12	5
# PCG in Major Subspecialty for trauma admissions	83	3

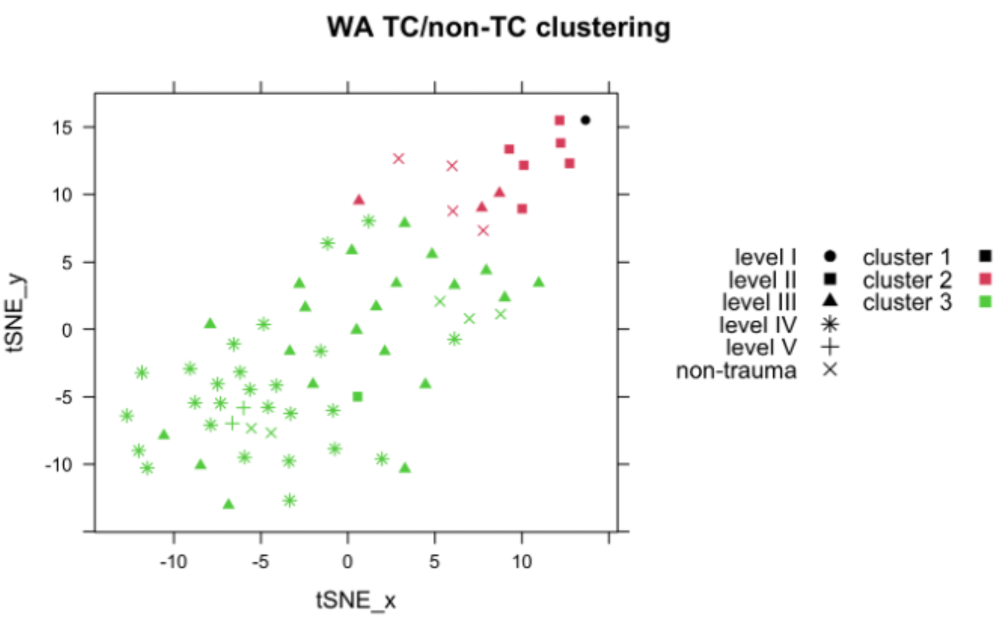


Figure B.3: Subgroup clustering results for general surgery

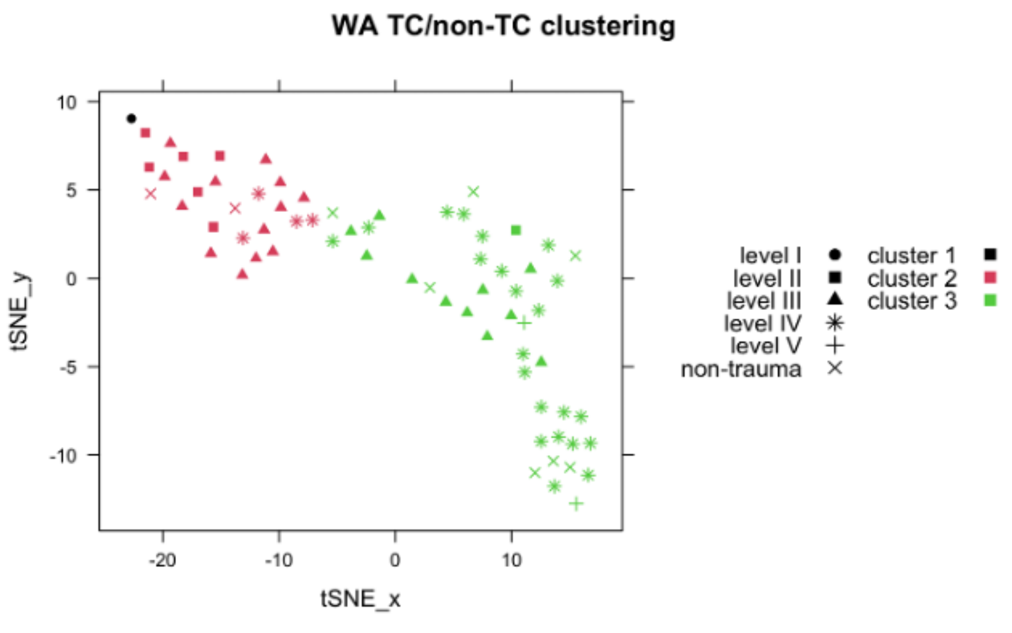


Figure B.4: Subgroup clustering results for orthopedics

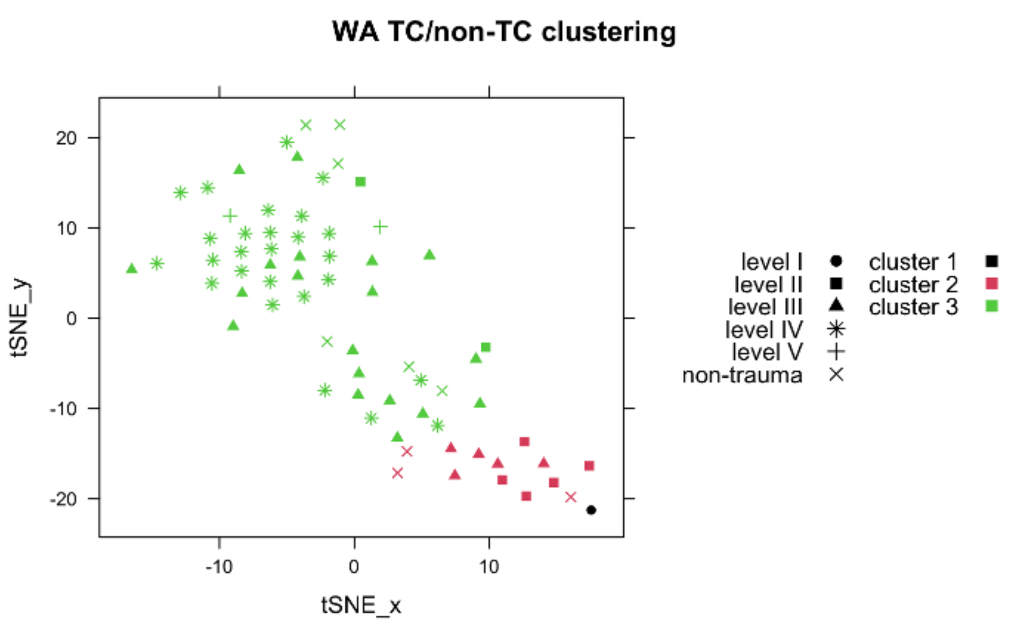


Figure B.5: Subgroup clustering results for neurosurgery

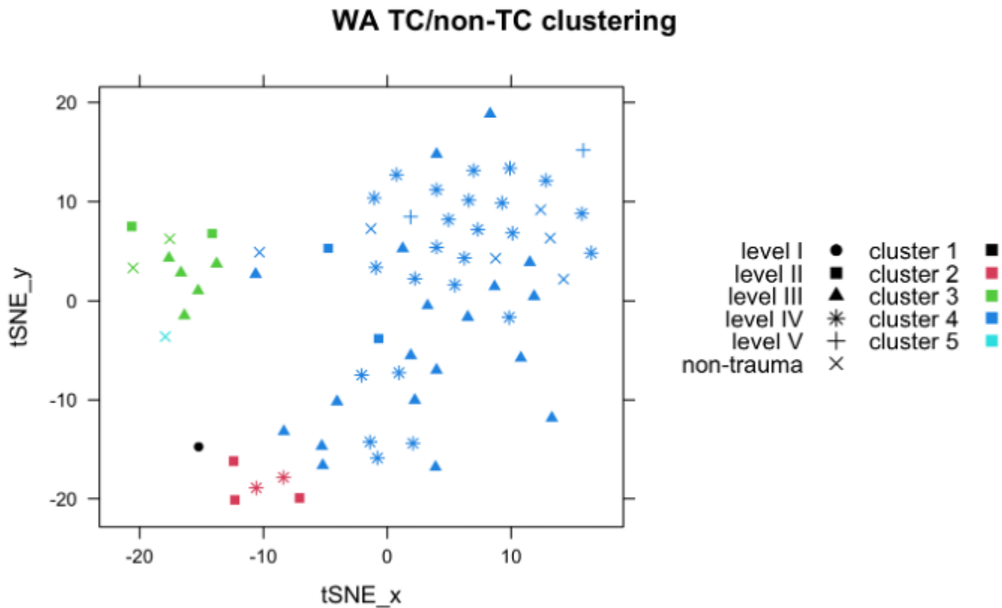


Figure B.6: Subgroup clustering results for urology

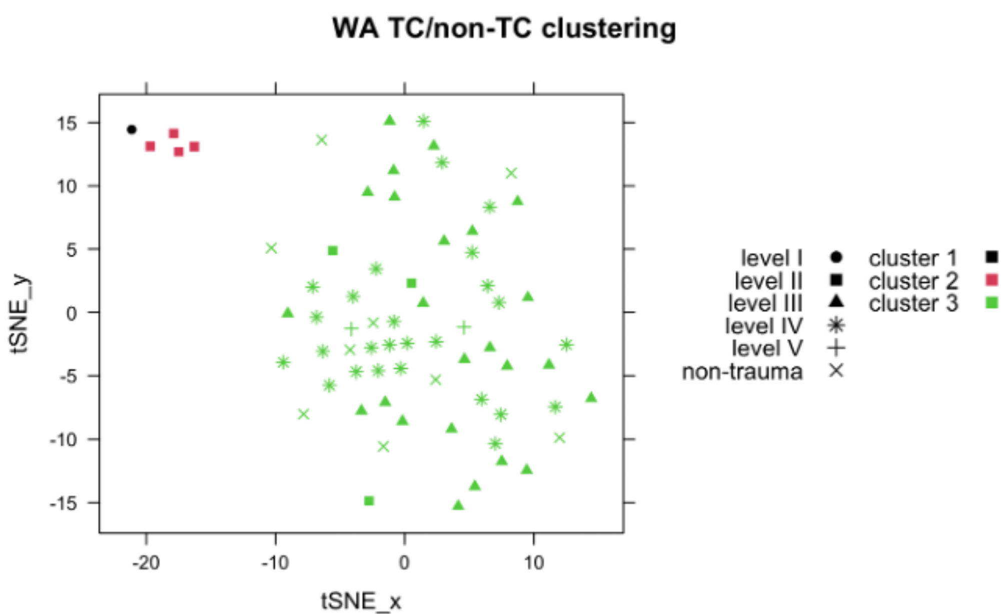


Figure B.7: Subgroup clustering results for subspecialty

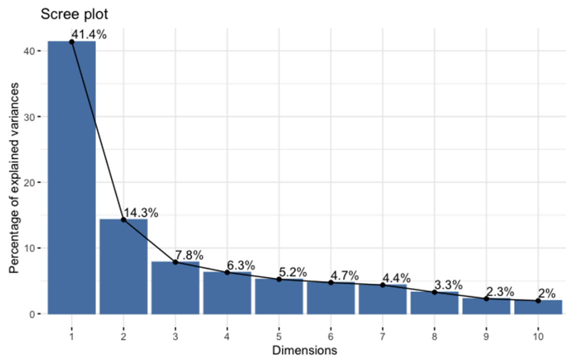


Figure B.8: PCA result of set 1

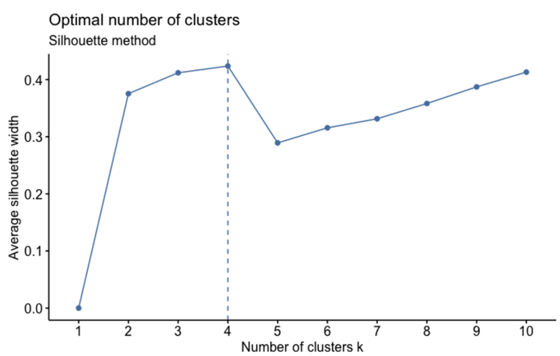


Figure B.9: Cluster number evaluation of set 1

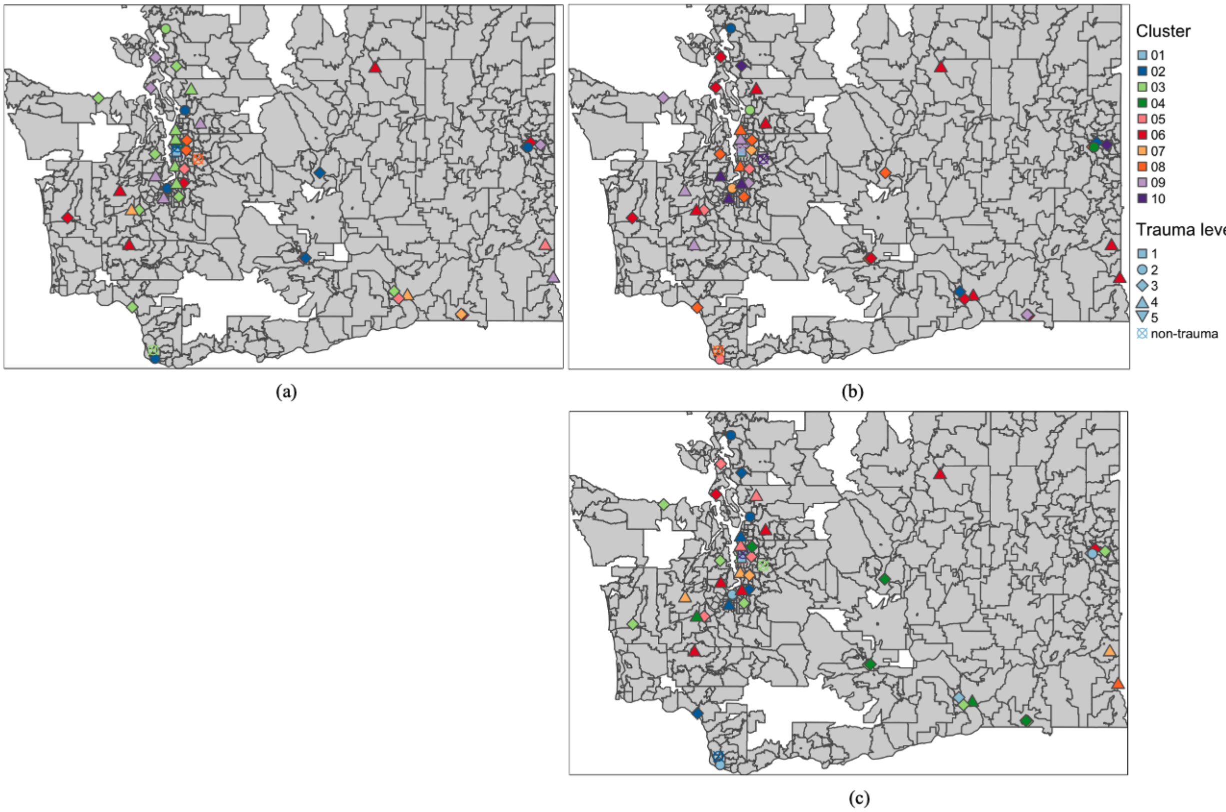


Figure B.10: Clustering results displayed on a map of WA: (a) Set 2 surgical care PCG distribution and other features clustering, (b) Set 3-1 surgical care volume clustering, (c) Set 3-2 surgical care distribution clustering

Note: The background of the map illustrates the division of zip codes within the state of Washington (WA). Each symbol on the map represents a hospital, where the geographic location is indicated by the symbol's placement. The color of the symbol represents the cluster to which the hospital belongs, and the shape denotes the designated trauma level.

Table B.9: Original features contributed to the TCs/non-TCs clusters from Set 1 surgical care procedure subgroup labels and other features clustering

Cluster	1	2	3	4	5	6	7	8	9	10

TC/non-TC levels in the cluster	I	II	II, III, Non	II, III	II, Non	III, IV, Non	III, IV, V, Non	III, Non	III, IV	III
# TC/non-TC in the cluster	1	3	5	3	3	12	26	4	10	2
Cluster mean										
Median age of trauma patients (year)	47	61	70	72	7	70	72	70	70	74
Median age of non-trauma patients (year)	55	50	47	57	8	54	56	61	34	57
# Trauma admissions	5605	1552	1345	688	182	601	173	378	37	545
% Trauma patients transferred out	1%	2%	1%	2%	2%	3%	6%	3%	27%	3%
Median ISS	9	9	4	4	3	4	4	7	4	4
SDI in TC/non-TC area	74	87	62	70	63	52	50	65	64	45
Mean SVI in trauma patient residence	0.51	0.56	0.39	0.49	0.55	0.56	0.52	0.47	0.78	0.45
Mean SVI in non-trauma patient residence	0.54	0.56	0.4	0.51	0.53	0.58	0.53	0.5	0.8	0.46
% Trauma patients with private payer	40%	34%	26%	21%	41%	31%	22%	25%	15%	18%
% Trauma patients with low-income payer	34%	25%	13%	13%	56%	12%	12%	12%	23%	10%
% Non-trauma patients with private payer	22%	35%	46%	30%	43%	39%	34%	35%	23%	30%
% Non-trauma patients with low-income payer	39%	31%	19%	25%	54%	22%	22%	15%	48%	25%

# Trauma MP	8025	1296	923	452	112	444	103	325	19	349
# Non-trauma MP	8730	13474	14318	6736	3113	4759	1406	10030	275	3602
% Trauma major General Surgery in all MP	13%	16%	10%	13%	7%	6%	5%	20%	11%	5%
% Trauma major Orthopedics in all MP	53%	58%	73%	74%	67%	83%	85%	40%	73%	85%
% Trauma major Neurosurgery in all MP	18%	16%	10%	9%	19%	6%	6%	34%	0	4%
% Non-trauma major General Surgery in all MP	23%	45%	36%	48%	33%	30%	31%	40%	17%	27%
% Non-trauma major Orthopedics in all MP	23%	15%	20%	16%	30%	29%	28%	12%	14%	35%
% Non-trauma major Neurosurgery in all MP	38%	13%	9%	9%	22%	10%	8%	29%	2%	5%
% Non-trauma other major procedures in all MP	1%	20%	29%	19%	0	23%	24%	9%	59%	25%
% TC/non-TC in General Surgery label 1	100%†	0	0	0	0	0	0	0	0	0
% TC/non-TC in General Surgery label 2^{a7}	0	100%	80%	100%	0	0	0	75%	0	0
% TC/non-TC in General Surgery label 3^{a4}	0	0	20%	0	100%	100%	100%	25%	100%	100%
% TC/non-TC in Orthopedics label 1	100%	0	0	0	0	0	0	0	0	0
% TC/non-TC in Orthopedics label 2^{a3,b1}	0	100%	100%	100%	0	100%	0	0	0	100%
% TC/non-TC in Orthopedics label 3^{a1,b2}	0	0	0	0	100%	0	100%	100%	100%	0

% TC/non-TC in Neurosurgery label 1	100%	0	0	0	0	0	0	0	0	0
% TC/non-TC in Neurosurgery label 2^{a6}	0	100%	100%	0	0	17%	0	75%	0	0
% TC/non-TC in Neurosurgery label 3^{a2}	0	0	0	100%	100%	83%	100%	25%	100%	100%
% TC/non-TC in Urology label 1	100%	0	0	0	0	0	0	0	0	0
% TC/non-TC in Urology label 2	0	100%	0	0	0	0	0.08	0	0	0
% TC/non-TC in Urology label 3^{c1}	0	0	80%	0	0	0	0	75%	0	100%
% TC/non-TC in Urology label 4^{a5}	0	0	0	100%	100%	100%	92%	25%	100%	0
% TC/non-TC in Urology label 5	0	0	20%	0	0	0	0	0	0	0
% TC/non-TC in Subspecialty label 1	100%	0	0	0	0	0	0	0	0	0
% TC/non-TC in Subspecialty label 2	0	100%	20%	0	0	0	0	0	0	0
% TC/non-TC in Subspecialty label 3	0	0	80%	100%	100%	100%	100%	100%	100%	100%

ai (i = 1, 2, . . . , 7): The top ith feature that contributes no less than 10% of the variation within the 1st principal component.

bi (i = 1, 2): The top ith feature that contributes no less than 10% of the variation within the 2nd principal component.

c1: The 1st and only feature that contributes no less than 10% of the variation within the 3rd principal component.

†: 100% percent of the TCs/non-TCs in cluster 1 are with general surgery label 1.

Abbreviations: ISS (Injury Severity Score); TC (Trauma Center); SDI (Social Deprivation Index); SVI (Social Vulnerability Index); MP (major therapeutic procedures); PCG (Procedure Complexity Group).

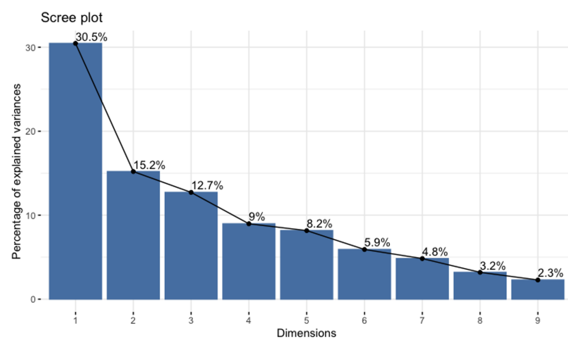


Figure B.11: PCA result of set 2

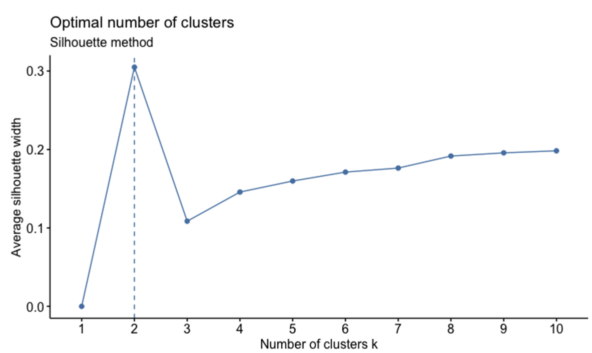


Figure B.12: Cluster number evaluation of set 2

Table B.10: Original features contributed to the TCs/non-TCs clusters from Set 2 surgical care PCG distribution and other features clustering

Cluster	1	2	3	4	5	6	7	8	9	10
TC/non-TC levels in the cluster	I	II, III, Non	II, III, IV, Non	II, Non	III, IV	III, IV	III, IV	III, Non	III, IV	Non
# TC/non-TC in the cluster	1	11	14	2	4	7	3	3	7	1
Cluster mean										
% Trauma patients who were male	69%	51%	44%	57%	46%	43%	50%	42%	43%	57%
% Non-trauma who were male	61%	45%	42%	54%	38%	39%	44%	38%	45%	53%
Median age of trauma patients (year)^{b2}	47	65	72	9	70	71	69	75	74	72
Median age of non-trauma patients (year)^{b1,c2}	55	54	56	6	38	52	60	43	62	66
# Trauma admissions^{d3}	5605	1042	547	270	434	225	188	784	235	495
% Trauma admissions	38%	5%	5%	4%	4%	6%	5%	5%	7%	5%
% Trauma patients transferred in	51%	10%	3%	16%	1%	2%	6%	6%	1%	46%
% Trauma patients transferred out	1%	2%	3%	3%	3%	7%	3%	2%	5%	3%
% Non-trauma patients transferred in	18%	8%	2%	11%	1%	1%	3%	5%	1%	23%
Median ISS	9	6	4	5	4	4	4	4	4	16

% Median ISS over 15 (severe injured)	40%	22%	11%	19%	11%	8%	13%	11%	6%	55%
% Trauma patients with a blunt mechanism	68%	71%	75%	57%	73%	79%	74%	75%	76%	75%
% Trauma patients with a penetrating mechanism	8%	4%	4%	11%	3%	2%	3%	2%	4%	0%
% Trauma patients with a burn mechanism	7%	0%	0%	1%	0%	0%	0%	0%	1%	0%
SDI in TC/non-TC area^{c3,d2}	74	82	46	62	63	66	56	24	41	61
Mean SVI in trauma patient residence^{c4}	0.51	0.53	0.5	0.53	0.59	0.66	0.63	0.3	0.43	0.4
Mean SVI in non-trauma patient residence^{c5}	0.54	0.55	0.51	0.52	0.6	0.66	0.62	0.3	0.45	0.44
% Trauma patients with private payer	40%	27%	27%	45%	40%	17%	32%	24%	22%	23%
% Trauma patients with low-income payer	34%	20%	12%	50%	5%	16%	13%	9%	11%	12%
% Non-trauma patients with private payer^{c1}	22%	34%	35%	42%	61%	20%	40%	56%	28%	31%
% Non-trauma patients with low-income payer	39%	26%	24%	54%	11%	39%	14%	13%	20%	13%
# Trauma MP	8025	792	374	166	319	154	162	516	149	436
# Non-trauma MP^{d1}	8730	11912	4401	4438	3997	1279	3130	8309	1310	11040
% Trauma major General Surgery in all MP	13%	16%	8%	11%	7%	4%	9%	7%	3%	19%
% Trauma major Orthopedics in all MP^{a1}	53%	62%	81%	62%	84%	92%	65%	77%	90%	2%

% Trauma major Neurosurgery in all MP	18%	14%	5%	15%	4%	0%	22%	10%	3%	76%
% Trauma major Subspecialty in all MP	15%	7%	5%	11%	3%	3%	2%	3%	3%	3%
% Non-trauma major General Surgery in all MP	23%	47%	38%	49%	22%	27%	13%	28%	24%	44%
% Non-trauma major Orthopedics in all MP	23%	17%	22%	15%	22%	27%	31%	18%	47%	3%
% Non-trauma major Neurosurgery in all MP	38%	12%	7%	15%	10%	2%	41%	12%	8%	49%
% Non-trauma major Urology in all MP	3%	5%	5%	5%	6%	5%	2%	4%	5%	0%
% Non-trauma major Subspecialty in all MP	11%	4%	3%	16%	2%	3%	1%	2%	3%	4%
% Non-trauma other major procedures in all MP	1%	16%	25%	0%	38%	35%	11%	35%	13%	0%
Percent of specific PCG in MP in trauma patients										
Joint, Extremities lower, 1	1%	2%	3%	4%	4%	5%	4%	5%	4%	0%
Joint, Extremities lower, 2	1%	6%	9%	0%	5%	11%	6%	8%	12%	0%
Joint, Extremities lower, 3	0%	2%	4%	0%	2%	5%	3%	4%	5%	0%
Joint, Extremities upper, 1	0%	2%	1%	0%	1%	1%	1%	1%	2%	0%
Open fixation, Extremities lower, 1	10%	11%	16%	11%	22%	20%	6%	12%	18%	0%
Open fixation, Extremities lower, 2	3%	6%	9%	7%	9%	12%	8%	8%	8%	0%
Open fixation, Extremities lower, 3	5%	7%	8%	4%	9%	10%	7%	8%	10%	0%

Other general surgery, Abdomen, 0	0%	1%	1%	1%	1%	0%	1%	1%	1%	0%
Percutaneous fixation, Extremities lower, 2	1%	3%	5%	2%	6%	7%	2%	6%	7%	0%
Spine procedures, Abdomen, 1	1%	2%	1%	0%	0%	0%	5%	2%	1%	18%

a1: The 1st and only feature that contributes no less than 10% of the variation within the 1st principal component.

bi (i = 1, 2): The top ith feature that contributes no less than 10% of the variation within the 2nd principal component.

ci (i = 1, 2, 3, 4, 5): The top ith feature that contributes no less than 10% of the variation within the 3rd principal component.

di (i = 1, 2, 3): The top ith feature that contributes no less than 10% of the variation within the 4th principal component.

Abbreviations: ISS (Injury Severity Score); TC (Trauma Center); SDI (Social Deprivation Index); SVI (Social Vulnerability Index); MP (major therapeutic procedures); PCG (Procedure Complexity Group).

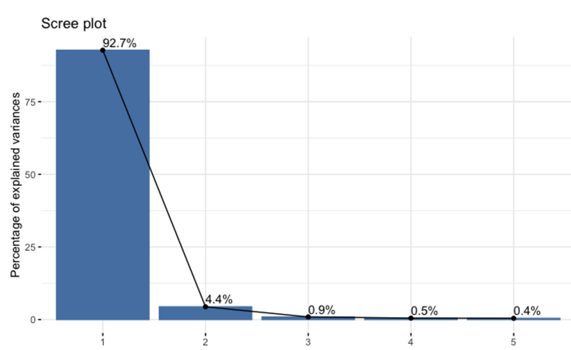


Figure B.13: PCA result of set 3-1

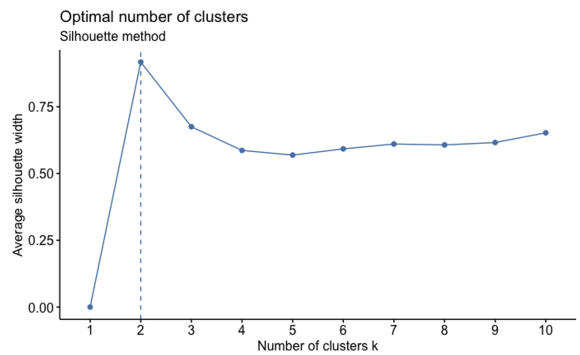


Figure B.14: Cluster number evaluation of set 3-1

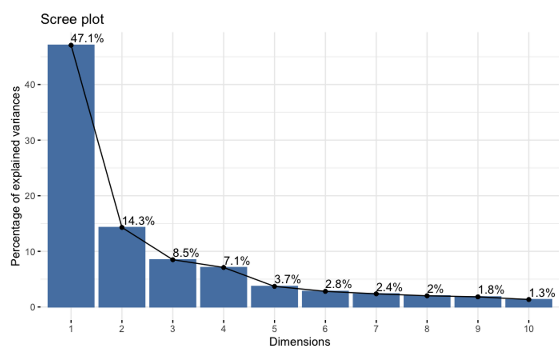


Figure B.15: PCA result of set 3-2

Table B.11: Original features contributed to the TCs/non-TCs clusters from set 3-1 surgical care volume clustering

Cluster	1	2	3	4	5	6	7	8	9	10
TC/non-TC levels in the cluster	I	II, III	II, Non	II	II, III	II, III, IV	II, III	III, IV, Non	III, IV, Non	III IV, Non

# TC/non-TC in the cluster	1	4	2	1	3	14	2	10	10	6
Cluster mean										
Number of specific renewed PCG in trauma patients										
Amputation, Extremities upper, minor	140	2	2	4	1	0	3	1	0	0.3
Craniotomy, Head, major	200	15	7	68	17	1	28	3	5	0
Ex fix, Extremities lower, minor	189	9	5	16	8	0.1	5	4	0.3	3
Facial fractures, Face, minor	145	7	6	45	9	0.2	18	1	1	0
Joint, Extremities lower, minor	137	50	159	121	83	13	96	49	21	35
Open fixation, Extremities lower, major^{a2}	511	51	103	185	91	8	66	37	13	24
Open fixation, Extremities lower, minor^{a1}	1069	131	252	390	224	20	166	95	36	65
Open fixation, Extremities upper, major	235	13	26	77	16	3	19	11	5	3
Open fixation, Extremities upper, minor	444	39	72	136	42	4	31	17	9	13
Open pelvis fixation, Extremities lower, minor	224	5	6	74	6	1	7	1	2	0.2
Other general surgery, Abdomen, major	166	11	11	32	12	2	19	2	3	1
Other ortho, Extremities lower, minor	164	14	34	38	25	2	14	10	4	5

Other ortho, Extremities upper, minor	232	12	28	29	14	2	22	7	2	3
Percutaneous fixation, Extremities lower, minor	156	32	32	93	29	7	39	33	10	19
Percutaneous pelvic fixation, Extremities lower, minor	146	1	0	23	2	0	0	0.1	0.1	0
Peripheral nerve, Extremities upper, minor	142	3	5	14	5	0.1	8	3	1	2
Reconstruction, Extremities lower, minor	234	7	13	20	14	2	5	5	3	4
Reconstruction, Extremities upper, minor	207	4	3	16	5	1	4	3	1	0.3
Spine procedures, Abdomen, minor	221	13	26	48	25	3	22	14	17	1
Spine procedures, Neck, major	318	12	13	37	12	1	29	4	12	0

ai (i = 1, 2): The top ith feature that contributes no less than 10% of the variation within the 1st principal component.

Table B.12: Original features contributed to the TCs/non-TCs clusters from set 3-2 surgical care volume clustering

Cluster	1	2	3	4	5	6	7	8	9	10
TC/non-TC levels in the cluster	I, III,	II, III,	III, Non	III, IV,	III, IV,	III, IV	III, IV	IV	Non	Non

	III, Non	IV, Non		Non	Non					
# TC/non-TC in the cluster	9	8	9	7	6	7	4	1	1	1
Cluster mean										
Percent of specific renewed PCG in MP in trauma patients										
Amputation, Extremities lower, minor	0.4%	0.3%	1%	0.3%	1%	0.4%	1%	0	0.2%	0
Cardiac, Chest, major	1%	0.3%	0.3%	0.4%	0.5%	0	1%	0	3%	4%
Cardiac, Chest, minor	1%	1%	1%	1%	1%	0.1%	0.3%	0	6%	8%
Control of hemorrhage, Abdomen, major	1%	0.4%	0.3%	2%	0.3%	0.1%	0.3%	0	0.2%	0.3%
Craniotomy, Head, major	3%	1%	0	1%	1%	0	1%	0	8%	1%
Craniotomy, Head, minor	1%	0.1%	0	0.5%	0.02%	0	0.04%	0	1%	1%
Ex fix, Extremities lower, minor	1%	1%	0.5%	1%	1%	1%	1%	0	0	0
Exploratory laparotomy/other abdominal surgery, Abdomen, major	1%	0.3%	0.4%	1%	0.1%	0	0.1%	0	0	0
Joint, Extremities lower, major	1%	4%	3%	3%	4%	6%	2%	11%	0	3%
Joint, Extremities lower, minor[b1]	5%	14%	15%	10%	16%	16%	10%	25%	0	4%
Joint, Extremities upper, major	1%	1%	1%	1%	1%	1%	3%	2%	0	6%
Joint, Extremities upper, minor	1%	1%	1%	2%	2%	0.4%	2%	9%	0	10%
Open fixation, Extremities lower, major	8%	10%	9%	7%	9%	11%	10%	13%	0	4%

Open fixation, Extremities lower, minor[a1,b2]	18%	27%	23%	15%	21%	33%	4%	15%	0	5%
Open fixation, Extremities upper, major	3%	3%	2%	4%	2%	2%	3%	0	0	3%
Open fixation, Extremities upper, minor	6%	6%	4%	3%	4%	6%	4%	4%	0	7%
Open pelvis fixation, Extremities lower, minor	2%	0.1%	0.05%	1%	1%	0	1%	0	1%	0
Other ent, Head, minor	1%	0.1%	0.04%	0.2%	0.01%	0	0.04%	0	1%	2%
Other general surgery, Abdomen, major	2%	1%	1%	2%	2%	0.5%	0.5%	0	0	0
Other general surgery, Abdomen, minor	1%	1%	2%	3%	1%	1%	1%	0	0.2%	8%
Other neuro, Head, major	1%	0.1%	0	0.3%	0.3%	0	0.1%	0	3%	1%
Other neuro, Head, minor	1%	0.1%	0	0.2%	0	0	0.1%	0	0	0
Other ortho, Extremities lower, major	0.5%	1%	0.4%	0.3%	0.3%	1%	1%	0	0	1%
Other ortho, Extremities lower, minor	2%	2%	2%	3%	3%	2%	3%	1%	0.2%	1%
Other ortho, Extremities upper, minor	2%	2%	1%	2%	3%	1%	2%	8%	0.2%	1%
Other thoracic, Chest, major	1%	0.2%	1%	0.4%	0.4%	0.5%	0.1%	0	0.2%	0.3%
Percutaneous fixation, Extremities lower, major[b4]	2%	3%	8%	3%	3%	5%	1%	1%	0	1%
Percutaneous fixation, Extremities lower, minor[b3]	4%	6%	12%	5%	4%	7%	4%	5%	0	3%

Percutaneous fixation, Extremities upper, minor	1%	0.3%	0.5%	1%	0.4%	0.4%	0	0	0	0.3%
Reconstruction, Extremities lower, minor	1%	2%	2%	2%	3%	1%	1%	2%	0	1%
Reconstruction, Extremities upper, minor	1%	1%	0.2%	1%	1%	0.3%	1%	1%	0	0.3%
Spine procedures, Abdomen, minor	2%	1%	1%	8%	4%	0.1%	1%	0	23%	2%
Spine procedures, Chest, minor	1%	0.2%	0.3%	2%	1%	0	0.2%	0	10%	3%
Spine procedures, Neck, major	2%	1%	0.2%	3%	1%	0	1%	0	17%	3%
Spine procedures, Neck, minor	1%	0.2%	0.1%	1%	1%	0	0.3%	0	7%	1%

a1: The only feature that contributes no less than 10% of the variation within the 1st principal component.

bi (i = 1, 2, 3, 4): The top ith feature that contributes no less than 10% of the variation within the 2nd principal component.

Appendix C
APPENDIX OF CHAPTER 4

Table C.1: Trauma care quality metrics

No.	Metric ID	Variable type	Value direction for better quality	Metric type	Description
1	3	numeric	lower	Timeliness	Time to first medical contact, min
2	4	numeric	lower	Timeliness	Prehospital time, min
3	6	binary	higher	Appropriateness	Intubation of unconscious patient
4	9	binary	lower	Appropriateness	Die in ED, with initial blood pressure, without REBOA or ED thoracotomy
5	11	binary	higher	Appropriateness	Airway secured in the ED
6	12	binary	higher	Appropriateness	Tracheal intubation
7	21	binary	higher	Timeliness	ED stay $<$ 1 hour for patients with GCS $<$ 9 or intubated
8	22	binary	higher	Timeliness	ED stay $<$ 1 hour for patient admitted to the ICU
9	26	binary	lower	Performance/Outcome	unplanned ICU admission
10	46	numeric	lower	Availability	ICU length of stay, day
11	47	numeric	lower	Availability	Length of stay, day
12	49	binary	lower	Performance	Complicaitons - all/total

13	50	binary	lower	Performance/Outcome	PE
14	51	binary	lower	Performance/Outcome	Mortality
15	52	binary	lower	Performance/Outcome	death $\leq$ 48 hours
16	53	binary	lower	Performance/Outcome	death within 1 hour ward arrival
17	54	binary	lower	Performance/Outcome	Failure to rescue
18	55	binary	lower	Performance/Outcome	death $>$ 48 hours
19	56	binary	lower	Performance/Outcome	TBI mortality
20	57	binary	lower	Performance/Outcome	Penetrating injury mortality
21	57001	binary	lower	Performance/Outcome	Penetrating injury mortality
22	57002	binary	lower	Performance/Outcome	Penetrating injury mortality
23	58	binary	lower	Performance/Outcome	Blunt trauma mortality - multisystem
24	59	binary	lower	Performance/Outcome	Blunt trauma mortality - single system
25	7	binary	higher	Performance	Pelvic binder in pelvic fracture
26	15	binary	higher	Performance	tetanus prophylaxis
27	18	binary	higher	Performance	E-FAST for patients without a CT
28	35	binary	higher	Performance	Enteral feeding of patients with TBI within 7 days
29	36	binary	higher	Performance	ICP monitoring in severe TBI with pathologic CT finding
30	80	count	higher	Resource	Soft tissue coverage expertise
31	84	binary	higher	Performance	Activation highest criteria – age specific hypotension
32	87	binary	higher	Performance	Activation highest criteria – patients receiving transfusion
33	93	count	higher	Resource	Emergency Airway Management
34	112	binary	higher	Resource	Fasciotomy rate
35	117	count	higher	Resource	Volume of geriatric hip fracture

36	118	binary	higher	Performance	Rate of surgery for geriatric hip fracture
37	132	binary	higher	Performance	Frequency and timing of repeat head CTs
38	137	binary	higher	Performance	MRI spine rates
39	138	binary	higher	Performance	Frequency of BCVI screeening
40	142	binary	higher	Performance	BCVI Screening for - C-spine fracture
41	143	binary	higher	Performance	BCVI Screening for - Basilar skull fracture
42	150	binary	higher	Performance	RUG rates
43	164	binary	higher	Performance	Spinal cord immobilization percentage
44	165	binary	higher	Performance	Low GCS (< 15) with spine immobilization
45	166	binary	higher	Performance	Longbone fractures with spine imobilization
46	179	binary	higher	Performance	ICP in GCS < 8 & CT with brain damage, includes swelling
47	186	binary	higher	Resource	IVC filter rate in TBI patients
48	222	binary	higher	Performance	Cervical spine injury with any respiratory distress
49	227	binary	higher	Resource	Penetrating extremity injury with tourniquet
50	233	binary	lower	Performance	Rate of spine immobilization with penetrating injuries
51	243	binary	higher	Performance	Rate of ED thoractomy in penetrating thoracic trauma

52	244	binary	higher	Performance	Rate of ED thoracotomy in blunt trauma
53	272	binary	higher	Resource	Tourniquet in place triage
54	10	binary	higher	Appropriateness	Trauma team activation
55	14	binary	higher	Appropriateness	Operative management for patients with penetrating GSW
56	17	numeric	lower	Timeliness	Time to cranial CT for patients with GCS < 14, min
57	28	numeric	lower	Timeliness	Time to first emergent surgery, min
58	29	binary	lower	Timeliness	Delay to ex-lap > 2 hours
59	31	numeric	lower	Timeliness	Time to surgery for patients in shock, min
60	38	binary	higher	Timeliness	Open long bone fracture surgery within 6 hours
61	40	binary	higher	Timeliness	Open fracture g 1-2 to OR within 16 hours
62	41	binary	higher	Timeliness	Open long bone fractures stabilized within 24 hours
63	48	binary	higher	Availability	Vent associated events
64	85	binary	higher	Appropriateness	Activation highest criteria – GSW to neck chest or abdomen
65	86	binary	higher	Appropriateness	Activation highest criteria – GCS <9
66	88	binary	higher	Appropriateness	Activation highest criteria – patients intubated in the field
67	89	binary	higher	Appropriateness	Activation highest criteria – Patients with respiratory compromise and need for urgent airway

68	92	binary	lower	Timeliness	Trauma surgeon present at the trauma > 15 min (level I/II) or 30 min (level III/IV)
69	92001	binary	lower	Timeliness	Trauma surgeon present at the trauma > 15 min (level I/II) or 30 min (level III/IV)
70	96	numeric	lower	Timeliness	Severe TBI - GCS < 9 with CT evidence of intra-cranial trauma, min
71	102	numeric	lower	Timeliness	Orthopedic consult time for severe extremity injury, min
72	106	binary	higher	Appropriateness	Open fractures with initial operation in the OR within 24 hours
73	111	binary	higher	Availability	Amputation proximal to wrist/ankle rate
74	116	binary	lower	Performance/Outcome	Rate of DVT in pelvic fracture
75	121	binary	higher	Timeliness	Femur stabilization within 24 hours
76	125	binary	higher	Performance/Outcome	Discharge to rehab for patients with fractures
77	129	binary	higher	Appropriateness	Activation highest criteria lower for older patients
78	131	binary	higher	Appropriateness	Discharge to rehab for older patients
79	148	binary	lower	Appropriateness	Rate of CT abdomen for unstable patient
80	151	binary	higher	Appropriateness	Completion spine imaging in patient with Cspine injury
81	155	binary	higher	Availability	Rate of extremity imaging
82	156	binary	higher	Availability	Rate of angioembolization
83	157	binary	higher	Availability	Rate of splenic angio

84	158	binary	higher	Availability	Rate of liver angio
85	168	binary	lower	Appropriateness	Percentage with plain film of the spine only
86	169	binary	higher	Availability	Rate of operative and non-operative management of c-spine fractures
87	171	binary	lower	Performance/Outcome	Rate of DVT in SCI
88	172	numeric	lower	Timeliness	Time to tracheostomy in SCI patients, min
89	173	binary	lower	Performance/Outcome	Decubitus ulcer rate in SCI patients
90	174	binary	higher	Performance/Outcome	Discharge location home for SCI patients
91	174001	binary	higher	Performance/Outcome	Discharge location rehab for SCI patients
92	174002	binary	lower	Performance/Outcome	Discharge location SNF for SCI patients
93	175	binary	higher	Performance/Outcome	Percent of the documentation of GCS
94	181	binary	higher	Availability	Rate of crani
95	184	binary	higher	Timeliness	Percentage of patiens with TBI and tracheostomy that are completed within 8 days
96	190	binary	higher	Availability	MTP
97	190001	binary	higher	Availability	MTP
98	190002	binary	higher	Availability	MTP
99	192	binary	higher	Appropriateness	Patients transfused in a 1:1 to 1:2 ratio
100	198	binary	lower	Availability	Ampuation rate for penetrating

101	203	binary	higher	Availability	Patient with hypotension/shock with penetrating abdominal trauma
102	205	binary	higher	Appropriateness	Rate of laparotomy for stab wounds to the abdomen in hd stable patients
103	214	binary	higher	Availability	Availability of emergent surgical airway
104	214001	binary	higher	Availability	Availability of emergent surgical airway
105	214002	binary	higher	Availability	Availability of emergent surgical airway
106	219	binary	higher	Appropriateness	Severe hemmorhagic shock
107	236	binary	higher	Availability	Rate of MRI with spine injuries
108	242	binary	lower	Availability	Rate of delayed angio for spleen > 24 hours
109	242001	binary	lower	Availability	Rate of delayed angio for spleen > 48 hours
110	255	numeric	lower	Timeliness	Time to tracheostomy, min
111	256	binary	higher	Timeliness	Early trach within 8 days
112	257	binary	lower	Timeliness	Late trach after 8 days
113	69	binary	higher	Timeliness	POCUS - 15 minutes
114	69001	binary	higher	Timeliness	POCUS - 15 minutes
115	70	binary	higher	Timeliness	Interventional radiology - 1 hour
116	71	binary	higher	Resource	MRI - 2 hours
117	250	binary	higher	Resource	EVD placement
118	16	binary	higher	Appropriateness	Antibiotics for open fractures
119	16001	binary	higher	Appropriateness	Antibiotics for open fractures within 24 hours

120	23	binary	higher	Availability	Activation of massive transfusion protovocl
121	25	binary	lower	Timeliness	Orthopedic response time > 30 min for emergent case
122	67	binary	higher	Timeliness	Convential radiology - in 15 min, level I/II; in 30 min, level III/IV
123	68	binary	higher	Timeliness	CT - in 15 min, level I/II; in 30 min, level III/IV
124	81	count	higher	Availability	Craniofacial expertise
125	177	binary	higher	Availability	Percentage of severe TBI with other injury
126	187	binary	higher	Appropriateness	Transfer rate of children with severe TBI
127	290	numeric	lower	Timeliness	Time to GS surgery, min
128	65	binary	higher	Availability	Orthopedic non-emergent availability

Table C.2: Trauma care quality metric relevant patients

No.	Metric ID	Description	Relevant patients	Relevant patients size
1	3	Time to first medical contact, min	All	121704
2	4	Prehospital time, min	ISS > 16	19568
3	6	Intubation of unconscious patient	GSC < 9	3956

4	9	Die in ED, with initial blood pressure, without REBOA or ED thoracotomy	Died in ED with documentable BP	1166
5	11	Airway secured in the ED	GCS $<$ 9	6077
6	12	Tracheal intubation	GCS $<$ 9	7121
7	21	ED stay $<$ 1 hour for patients with GCS $<$ 9 or intubated	GCS $<$ 9 or intubated	9705
8	22	ED stay $<$ 1 hour for patient admitted to the ICU	Admitted to the ICU from ED	30539
9	26	unplanned ICU admission	ICU admission	39670
10	46	ICU length of stay, day	ICU admission	39670
11	47	Length of stay, day	ICU admission	39670
12	49	Complicaitons - all/total	All	121704
13	50	PE	All	121704
14	51	Mortality	All	121704
15	52	death $\leq$ 48 hours	All	121704
16	53	death within 1 hour ward arrival	Admitted to ward from the ED	51754
17	54	Failure to rescue	Specific complications	2072
18	55	death $>$ 48 hours	Died	4607
19	56	TBI mortality	Severe TBI	21858
20	57	Penetrating injury mortality	Penetrating injuries	8135
21	57001	Penetrating injury mortality	Penetrating injuries and ISS $\geq$ 15	1990
22	57002	Penetrating injury mortality	Penetrating injuries and ISS $\geq$ 25	1160
23	58	Blunt trauma mortality - multisystem	Multisystem blunt trauma	31978

24	59	Blunt trauma mortality - single system	Single system blunt trauma	67628
25	7	Pelvic binder in pelvic fracture	Pelvic fracture	3597
26	15	tetanus prophylaxis	All	121704
27	18	E-FAST for patients without a CT	Abdominal injury, FAST and no CT scan of abdomen	3674
28	35	Enteral feeding of patients with TBI within 7 days	Severe TBI	21858
29	36	ICP monitoring in severe TBI with pathologic CT finding	Severe TBI	21858
30	80	Soft tissue coverage expertise	Extremity injuries	24686
31	84	Activation highest criteria – age specific hypotension	Age appropriate hypotension	5769
32	87	Activation highest criteria – patients receiving transfusion	Pre-hospital blood	1150
33	93	Emergency Airway Management	All	121704
34	112	Fasciotomy rate	Severe extremity injury	15399
35	117	Volume of geriatric hip fracture	Age > 65	51124
36	118	Rate of surgery for geriatric hip fracture	Age > 65 with diagnosis of hip fracture	5818
37	132	Frequency and timing of repeat head CTs	Head CT and severe_head	17163
38	137	MRI spine rates	C-spine injury	10747
39	138	Frequency of BCVI screeening	All	121704
40	142	BCVI Screening for - C-spine fracture	C-spine fractures	8627
41	143	BCVI Screening for - Basilar skull fracture	Basilar skull fractures	3895
42	150	RUG rates	Pelvic fracture	3597

43	164	Spinal cord immobilization percentage	All	121704
44	165	Low GCS (< 15) with spine immobilization	GCS < 15	20972
45	166	Longbone fractures with spine imobilization	Longbone fractures	17012
46	179	ICP in GCS < 8 & CT with brain damage, includes swelling	GCS < 8 and severe_head	3338
47	186	IVC filter rate in TBI patients	Severe TBI	21858
48	222	Cervical spine injury with any respiratory distress	C-spine injury and RR > 22	1208
49	227	Penetrating extremity injury with tourniquet	Penetrating mechanism and AIS ext > 1	2691
50	233	Rate of spine immobilization with penetrating injuries	Penetrating injuries	8135
51	243	Rate of ED thoractomy in penetrating thoracic trauma	Penetrating mechanism and chest ais > 2	1470
52	244	Rate of ED thoracotomy in blunt trauma	Blunt trauma and hypotension/shock	11001
53	272	Tourniquet in place triage	All	121704
54	10	Trauma team activation	Hypotension/shock or scene intubation	14348
55	14	Operative management for patients with penetrating GSW	Penetrating abdominal injury from firearm	1061
56	17	Time to cranial CT for patients with GCS < 14, min	GCS < 14	14711
57	28	Time to first emergent surgery, min	Received an operation	115854
58	29	Delay to ex-lap > 2 hours	Require Ex-lap	2304

59	31	Time to surgery for patients in shock, min	Shock and had surgery within 24 hours	10109
60	38	Open long bone fracture surgery within 6 hours	Open long bone fractures	4825
61	40	Open fracture g 1-2 to OR within 16 hours	G1 or g2 open fractures	6588
62	41	Open long bone fractures stabilized within 24 hours	Open long bone fractures	4825
63	48	Vent associated events	ICU and intubated	6611
64	85	Activation highest criteria – GSW to neck chest or abdomen	GSW to neck chest or abdomen	1571
65	86	Activation highest criteria – GCS ¡ 9	GCS $<$ 9	4361
66	88	Activation highest criteria – patients intubated in the field	Intubated in the field	1332
67	89	Activation highest criteria – Patients with respiratory compromise and need for urgent airway	Respiratory compromise	4237
68	92	Trauma surgeon present at the trauma $>$ 15 min (level I/II) or 30 min (level III/IV)	All	121704
69	92001	Trauma surgeon present at the trauma $>$ 15 min (level I/II) or 30 min (level III/IV)	Highest activation level	67292
70	96	Severe TBI - GCS $<$ 9 with CT evidence of intra-cranial trauma, min	Severe TBI and GCS $<$ 9	3614
71	102	Orthopedic consult time for severe extremity injury, min	Severe extremity injury	15399

72	106	Open fractures with initial operation in the OR within 24 hours	Open fractures with initial operation in the OR	1064
73	111	Amputation proximal to wrist/ankle rate	Severe extremity injury	15399
74	116	Rate of DVT in pelvic fracture	Pelvic fracture	3597
75	121	Femur stabilization within 24 hours	Femur fracture	11262
76	125	Discharge to rehab for patients with fractures	Longbone fracture and extremity AIS ≥ 2	17012
77	129	Activation highest criteria lower for older patients	Age > 65 with initial SBP *leq* 110	4286
78	131	Discharge to rehab for older patients	Age > 65 discharged alive	48860
79	148	Rate of CT abdomen for unstable patient	Shock	11426
80	151	Completion spine imaging in patient with Cspine injury	C-spine fractures	8627
81	155	Rate of extremity imaging	All	121704
82	156	Rate of angioembolization	All	121704
83	157	Rate of splenic angio	All	121704
84	158	Rate of liver angio	All	121704
85	168	Percentage with plain film of the spine only	Spine x-ray	1361
86	169	Rate of operative and non-operative management of c-spine fractures	C-spine fractures	8627
87	171	Rate of DVT in SCI	Spinal cord injury	6020
88	172	Time to tracheostomy in SCI patients, min	Spinal cord injury	6020

89	173	Decubitus ulcer rate in SCI patients	Spinal cord injury	6020
90	174	Discharge location home for SCI patients	Spinal cord injury	6020
91	174001	Discharge location rehab for SCI patients	Spinal cord injury	6020
92	174002	Discharge location SNF for SCI patients	Spinal cord injury	6020
93	175	Percent of the documentation of GCS	All	121704
94	181	Rate of crani	Severe TBI	21858
95	184	Percentage of patiens with TBI and tracheostomy that are completed within 8 days	Severe TBI	21858
96	190	MTP	All	121704
97	190001	MTP	ISS > 16	19568
98	190002	MTP	At least one transfusion	1940
99	192	Patients transfused in a 1:1 to 1:2 ratio	MTP	1951
100	198	Ampuation rate for penetrating	Penetrating extremity injuries	5313
101	203	Patient with hypotension/shock with penetrating abdominal trauma	Penetrating severe abdominal injuries	2053
102	205	Rate of laparotomy for stab wounds to the abdomen in hd stable patients	Penetrating abdominal injuries and no hypotension or shock	1208
103	214	Availability of emergent surgical airway	All	121704

104	214001	Availability of emergent surgical airway	All	121704
105	214002	Availability of emergent surgical airway	All	121704
106	219	Severe hemmorhagic shock	Hypotension/shock and MTP	1253
107	236	Rate of MRI with spine injuries	Spine fracture or spinal cord injury	24023
108	242	Rate of delayed angio for spleen > 24 hours	Spleen injury	2830
109	242001	Rate of delayed angio for spleen > 48 hours	Spleen injury	2830
110	255	Time to tracheostomy, min	Tracheostomy	8846
111	256	Early trach within 8 days	Tracheostomy	8846
112	257	Late trach after 8 days	Tracheostomy	8846
113	69	POCUS - 15 minutes	All	121704
114	69001	POCUS - 15 minutes	Hypotension	5769
115	70	Interventional radiology - 1 hour	Angiography within 24 hours	1272
116	71	MRI - 2 hours	MRI of the brain or spine	4175
117	250	EVD placement	Severe TBI	21858
118	16	Antibiotics for open fractures	Open fractures	6805
119	16001	Antibiotics for open fractures within 24 hours	Open fractures	6805
120	23	Activation of massive transfusion protovocl	Bleeding and shock	10665
121	25	Orthopedic response time > 30 min for emergent case	Emergent orthopedic proc	2049
122	67	Convential radiology - in 15 min, level I/II; in 30 min, level III/IV	ISS $\geq$ 16	21164

123	68	CT - in 15 min, level I/II; in 30 min, level III/IV	ISS $\geq$ 16	21164
124	81	Craniofacial expertise	Facial fracture repair	2681
125	177	Percentage of severe TBI with other injury	All	121704
126	187	Transfer rate of children with severe TBI	Age < 18 and severe TBI	1812
127	290	Time to GS surgery, min	Surgery within 48 hours that were not fracture repair, angio or crani	112702
128	65	Orthopedic non-emergent availability	All	121704

Table C.3: Individual-level summary on remaining trauma care quality metrics

No.	Metric ID	Min	1st quantile	Median	Mean	3rd quantile	Max	Number of missing	Proportion of missing
1	3	0	7	9	15.51	13	1507	47816	46%
2	4	4	35	48	165.8	68	26145	92649	90%
3	46	1	1	2	3.75	4	171	67771	66%
4	47	0	3	5	7.81	9	203	67883	66%
5	17	0	17	28	235.8	57	88956	94918	92%
6	28	0	13	44	268.7	153	73164	10288	10%
7	31	0	9	20	94.75	76	1437	95671	93%
8	172	0	28	660.5	3737.8	4479.5	37229	102728	99%
9	255	0	11	39	2155	1247	54113	96585	93%
10	290	0	11	39	174	140	2879	7270	7%

11	93	0	0	0	0.05	0	3	0	0%
12	117	0	0	0	0.12	0	6	56865	55%
13	81	1	1	2	1.88	2	10	101036	98%
14	6	0	0	0	0.09	0	1	100104	97%
15	9	0	0	1	0.74	1	1	102622	99%
16	11	0	0	1	0.73	1	1	99134	96%
17	12	0	1	1	0.99	1	1	98841	96%
18	21	0	0	0	0.4	1	1	95500	92%
19	22	0	0	0	0.14	0	1	75872	73%
20	26	0	0	0	0.07	0	1	67771	66%
21	49	0	0	0	0.07	0	1	0	0%
22	50	0	0	0	0	0	1	0	0%
23	51	0	0	0	0.04	0	1	0	0%
24	52	0	0	0	0.02	0	1	8	0%
25	53	0	0	0	0	0	1	58874	57%
26	54	0	0	0	0.24	0	1	101469	98%
27	55	0	0	0	0.42	1	1	99585	96%
28	56	0	0	0	0.1	0	1	84360	82%
29	57	0	0	0	0.12	0	1	96826	94%
30	57001	0	0	0	0.39	1	1	101812	99%
31	57002	0	0	1	0.55	1	1	102470	99%
32	58	0	0	0	0.05	0	1	74697	72%
33	59	0	0	0	0.02	0	1	45642	44%
34	7	0	0	0	0.02	0	1	100144	97%
35	15	0	0	0	0	0	1	0	0%
36	18	0	0	0	0.19	0	1	100301	97%
37	35	0	0	0	0.01	0	1	84360	82%
38	36	0	0	0	0.04	0	1	84360	82%
39	84	0	1	1	0.79	1	1	98728	96%

40	87	0	1	1	0.89	1	1	102465	99%
41	112	0	0	0	0	0	1	90273	87%
42	118	0	0	0	0.02	0	1	98195	95%
43	132	0	0	0	0.03	0	1	87933	85%
44	137	0	0	0	0	0	1	93733	91%
45	138	0	0	0	0.03	0	1	0	0%
46	142	0	0	0	0.13	0	1	95496	92%
47	143	0	0	0	0.12	0	1	100036	97%
48	150	0	0	0	0	0	1	100144	97%
49	164	0	0	0	0	0	1	0	0%
50	165	0	0	0	0	0	1	85294	83%
51	179	0	0	0	0.17	0	1	100516	97%
52	186	0	0	0	0.01	0	1	84360	82%
53	222	0	0	0	0.02	0	1	102315	99%
54	227	0	0	0	0	0	1	101098	98%
55	243	0	0	0	0.25	1	1	102230	99%
56	244	0	0	0	0.01	0	1	94598	92%
57	272	0	0	0	0	0	1	0	0%
58	10	0	1	1	0.76	1	1	92468	89%
59	38	0	0	0	0.2	0	1	99181	96%
60	40	0	0	0	0.28	1	1	97702	95%
61	41	0	0	0	0.47	1	1	99181	96%
62	48	0	0	0	0.01	0	1	97656	94%
63	86	0	1	1	0.94	1	1	99818	97%
64	88	0	1	1	0.98	1	1	102236	99%
65	89	0	1	1	0.79	1	1	99796	97%
66	92	0	1	1	0.93	1	1	63108	61%
67	92001	0	1	1	0.89	1	1	83023	80%
68	111	0	0	0	0.01	0	1	90273	87%

69	116	0	0	0	0.01	0	1	100144	97%
70	121	0	0	0	0.29	1	1	93820	91%
71	125	0	0	1	0.63	1	1	90681	88%
72	129	0	0	1	0.61	1	1	96629	93%
73	131	0	0	1	0.61	1	1	61139	59%
74	148	0	0	1	0.52	1	1	94406	91%
75	151	0	0	0	0.44	1	1	95496	92%
76	155	0	0	0	0.04	0	1	0	0%
77	156	0	0	0	0.01	0	1	0	0%
78	157	0	0	0	0	0	1	0	0%
79	158	0	0	0	0	0	1	0	0%
80	169	0	0	0	0.12	0	1	95496	92%
81	171	0	0	0	0.01	0	1	97886	95%
82	173	0	0	0	0.02	0	1	97886	95%
83	174	0	0	0	0.37	1	1	98214	95%
84	174001	0	0	0	0.29	1	1	98214	95%
85	174002	0	0	0	0.23	0	1	98214	95%
86	175	0	0	0	0.05	0	1	0	0%
87	181	0	0	0	0.03	0	1	84360	82%
88	184	0	0	0	0.13	0	1	84360	82%
89	190	0	0	0	0.02	0	1	21	0%
90	190001	0	0	0	0.07	0	1	86203	83%
91	190002	0	0	0	0.32	1	1	101711	98%
92	192	0	0	0	0.11	0	1	101717	98%
93	198	0	0	0	0.01	0	1	99016	96%
94	203	0	0	0	0.5	1	1	101795	98%
95	205	0	0	0	0.26	1	1	102340	99%
96	214	0	0	0	0.04	0	1	0	0%
97	214001	0	0	0	0.04	0	1	0	0%

98	214002	0	0	0	0.05	0	1	0	0%
99	219	0	0	0	0.31	1	1	102313	99%
100	236	0	0	0	0	0	1	81713	79%
101	256	0	1	1	0.94	1	1	96585	93%
102	257	0	0	0	0.06	0	1	96585	93%
103	69	0	0	0	0.22	0	1	0	0%
104	69001	0	0	0	0.33	1	1	98604	95%
105	70	0	0	0	0.17	0	1	102279	99%
106	71	0	0	0	0.01	0	1	99857	97%
107	250	0	0	0	0.04	0	1	84360	82%
108	16	0	0	0	0.48	1	1	97509	94%
109	16001	0	1	1	0.9	1	1	100309	97%
110	23	0	0	0	0.44	1	1	102193	99%
111	67	0	0	0	0.03	0	1	84851	82%
112	68	0	0	0	0.17	0	1	84851	82%
113	177	0	0	0	0.18	0	1	0	0%
114	187	0	0	0	0.28	1	1	102445	99%
115	65	0	0	0	0.03	0	1	0	0%

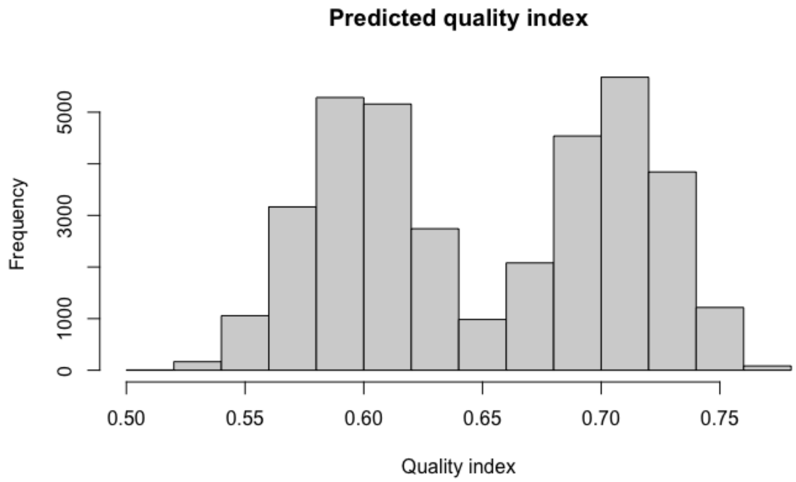


Figure C.1: Histogram of predicted quality index

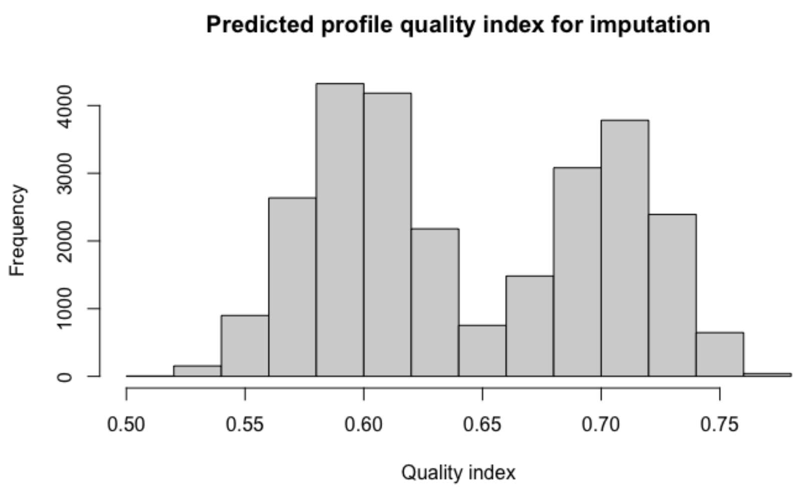


Figure C.2: Histogram of predicted profile quality index for imputation