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Critical Care in a Healthcare Crisis: Applying Reliability and Microsimulation Methods to Understand Implications of a Proposed Resource Allocation Policy

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to Understand Implications of a Proposed Resource Allocation Policy

A dissertation submitted in partial satisfaction of the

requirements for the degree of Doctor of Philosophy

in Health Policy and Management

by

Iheanacho Obinnaya Emeruwa

2023

ABSTRACT OF THE DISSERTATION

Critical Care in a Healthcare Crisis:
Applying Reliability and Microsimulation Methods
to Understand Implications of a Proposed Resource Allocation Policy

by

Iheanacho Obinnaya Emeruwa
Doctor of Philosophy in Health Policy and Management
University of California, Los Angeles, 2023
Professor Moira Inkelas, Chair

The COVID-19 pandemic demonstrated the potential for healthcare systems to lack capacity to meet demand for critical care in times of crisis. Recent research suggests a rise in the utilization of intensive care unit (ICU) resources and the potential misallocation of resources to patients without clinical need or hope of benefit. Several authorities have published resource allocation policies to guide healthcare systems, commonly relying on measures of illness severity to determine the priority by which ICU resources would be allocated. This raises concerns about the properties of and the potential for allocation criteria to exacerbate racial disparities in clinical outcomes. Policymakers intend that such policies would maximize the number of lives saved by prioritizing provision of critical care services to patients most likely to benefit. This dissertation examines the interrater reliability of the University of California's Scarce Resource Allocation Policy (SRAP) in determining the allocation priority of a cohort of consecutively admitted ICU patients at the University of California, Los Angeles (UCLA) Health System. Use of the SRAP had relatively poor reliability in determining allocation priority as laid out within the policy itself. A microsimulation model examined the likely impact of allocation decisions and likelihood of allocation of resources under four defined scenarios of resource constraint, for the outcome of ICU mortality. Mortality differed significantly across tested constraint levels compared to the

case of no constraint (i.e., current capacity). Mortality was greater in subgroups with lower priority for constrained ICU resources. A mediation analysis examined if observed differences in mortality risk among racial groups are related to the use of SOFA scores or the selected comorbid conditions. Results suggest that these policy criteria do not mediate the effect of race on mortality. Understanding the projected outcomes related to use of these policies and the policy criteria that drive observed differences among patient groups can better inform policymakers in shaping protocols to maximize lives saved and avoid worsening healthcare disparities.

The dissertation of Iheanacho Obinnaya Emeruwa is approved.

Onyebuchi Arah

Beth Glenn

Michael Ong

Russell Buhr

Moira Inkelas, Committee Chair

University of California, Los Angeles

2023

Dedication

For my parents and siblings, who have always given me the encouragement and perspective I

have needed to maximize the value of my education for the betterment of society – and myself.

Table of Contents

List of Tables and Figures

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Finally, I am indebted to my dissertation committee for the support and encouragement they gave me throughout this graduate degree. Even more than your wisdom, I sincerely appreciate all the time you spent hearing me think out loud and steering me toward better science. If I learned nothing else from this degree, I will have learned more about the goodness of others and for that, I will always be grateful.

Vita/Biographical Sketch

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Chapter 1: Background

Current Research and Emerging Issues in Critical Care Resource Allocation

The arrival of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the novel coronavirus that causes COVID-19, has led to the pandemic in the United States and around the world that has rivaled the Spanish influenza pandemic of the early 20th century. The World Health Organization (WHO) declared a COVID-19 pandemic on March 11, 2020.[1] This declaration was shortly followed by declarations of states of emergency in the state of California and in the United States of America.[2,3] As the scientific and medical communities worked rapidly to better understand the pathogenesis of this virus, healthcare systems both domestically and abroad have found themselves overwhelmed by the number of patients. One of the most well-known scenarios occurred in Lombardi, Italy as described by Grasselli and colleagues, where the healthcare system created almost 500 intensive care unit (ICU) beds in less than three weeks to address sharp increases in demand for critical care.[4]

Even prior to the COVID-19 pandemic, there has been a documented rise in the use of critical care resources. While professional societies have published and actively maintained guidelines to ensure effective allocation of critical care beds,[5] recent literature suggests that such guidelines have been ineffective. In 2015, Ward and Chong described a concerning trend in ICU utilization over the past 50 years – resources being allocated both to patients who may not need them and to patients who may not benefit from them.[6] Given the observed experiences both domestically and internationally, the University of California (UC) sought to develop a critical care resource allocation system to be implemented in the event of a crisis in which supply of resources is outstripped by demand ("surge conditions"). In developing the intervention, the organization operated under the causal hypothesis that misallocation of critical care resources in the setting of resource limitation (such as that imposed by a pandemic) will

lead to increasing mortality due to inability to provide necessary treatment. The intervention

hypothesis is that a standardized critical care triage and resource allocation protocol will

improve resource utilization by allocating resources to the patients in highest need with highest

likelihood of benefit, thus stabilizing or reducing critical care mortality.

Existing Policies and Tools in Scarce Resource Allocation

With the assistance of UCLA Library Services, I conducted an exhaustive review of multiple

literature databases in search of previous work examining tools used for scarce resource

allocation. Although many resource allocation policies exist, there is little to no literature on the

operationalization of such policies through the electronic medical record or otherwise. While the

COVID-19 pandemic has prompted a focus in the discussion of resource allocation in the field of

critical care, the dilemma that is resource allocation in healthcare has been considered long

before this crisis event. Literature databases reveal publications on health care resource

allocation as far back as the 1907s, but the most relevant work to the scenarios considered in

this dissertation appear in the early 2000s, around the time of the H1N1 influenza pandemic.

Many of these publications consider the many ethical principles that potentially guide resource

allocation policies. While the ethics of resource allocation is beyond the scope of this work, it is

important to highlight the role these principles have played in the development of the policies

that influence population-level health care decisions.

In one review of these ethical principles, Persad and colleagues suggest considering

eight ethical principles grouped into four categories reflecting the core ethical values underlying

the principles.[7] These four ethical values are: treating people equally, favoring the worst off,

maximizing total benefit, and promoting and rewarding social usefulness. As the authors note,

each of these eight principles is insufficient in that they will ignore morally relevant facts to the

decision-making process. Thus, they advocate for multi-principle strategies to achieve a just

framework for allocation. Building on this, White and colleagues propose a multi-principle

strategy for prioritization of ventilator and critical care bed allocation based on "patients' likelihood of surviving to hospital discharge" as determined by an "objective measure of acute illness severity" and on "patients' likelihood of achieving longer-term survival" as influenced by the "presence or absence of comorbid conditions that influence survival."[8] In making these recommendations, it is worth acknowledging that the authors take care not to make any categorical exclusions, noting that without clear justification as to how these patients are "ethically different" from others seeking critical care, such exclusions are ethically flawed. The UC policy is largely modeled on this framework.

Development of the University of California Scarce Resource Allocation Policy

The University of California tasked a multidisciplinary committee of clinicians and clinical ethicists, formed as the University of California Critical Care Bioethics Working Group, to develop guidelines for the Allocation of Scarce Critical Resources under Crisis Standards of Care (CSC), heretofore referred to as the Scarce Resource Allocation Policy (SRAP). The goal of this policy, explicitly designed to be implemented in surge conditions, is to standardize the process by which all critical care beds are allocated to patients who require such care. While the impetus for drafting the policy was the rapid arrival of the COVID-19 pandemic, the policy itself was designed to be used in any surge conditions (e.g., natural disaster with mass injuries). The intervention to be evaluated consists of three (3) major components, each considered necessary but not individually sufficient to achieve the stated goal of maximizing the number of lives saved.

Prioritization Algorithm to Determine Triage Category

The foundation of the SRAP is the prioritization algorithm. This algorithm has been codified in a document, based on literature review of recommendations of major medical societies and other systems' experiences, that is shared with the entire health system community. The Policy aims to optimize provision of critical care resources by applying consistent criteria by which all

patients are evaluated. The key outcome resulting from application of the prioritization algorithm is the Triage Category, a value by which patients are prioritized for allocation of critical care resources. There are six (6) such categories, in order of priority: Violet, Red, Orange, Yellow, Blue, and Green. Patients within the Violet category are deemed to have met one of a finite number of criteria that temporarily exempts them from the triage process, thereby giving them top priority for available resources. Patients within the Green category, under crisis standards of care, do not meet criteria for consideration of critical care and are managed outside of the ICU. Patients within the Blue category have an "acute catastrophic condition" that portends an extremely high risk of death and are systematically de-prioritized, receiving critical care resources only after all other patients have been allocated. Patients within all other categories are allocated resources as available according to priority.

To determine these remaining categories, the Policy requires the calculation of a Triage Allocation Score. This score is a summation of points contributed by the Sequential Organ Failure Assessment (SOFA) score, the objective measure of illness severity as suggested by White and colleagues, and the presence of any one of a defined set of chronic medical conditions, recommended by White and colleagues. The SOFA score was originally published in 1996 as a concise way of describing multiple organ dysfunction among six organ systems: respiratory, coagulation, liver, cardiovascular, central nervous system, and renal. It is worth noting here that the SOFA score was originally intended to be a descriptive, not predictive, tool used to complement existing scoring systems in patients with sepsis.[9] Since its origin, however, the SOFA score has been validated as an assessment of multiple organ system dysfunction associated with mortality and useful over time in predicting such outcomes in ICU patients, particularly early in their course.[10,11] Each of the organ system domains is assigned a score from 0 to 4, the sum of which results in the overall SOFA score ranging from 0 to 24. Modified versions of the SOFA score that are less reliant on laboratory values, thus simplifying

4

calculation and application in resource-constrained settings, have been shown to perform well in comparison to the originally derived SOFA score.[12]

Based on this, the SRAP leverages the SOFA or modified SOFA (mSOFA) as an objective indicator of "current overall clinical status" in its "multi-principle strategy to allocate critical care resources during crisis."[13] The SOFA score contributes between one and four points to the Triage Allocation Score. The other principle in this strategy calls for identification of "co-occurring conditions that moderate mortality." These conditions are divided into so-called "major comorbid conditions" and "severely life-limiting conditions" that contribute two or four points to the Triage Allocation Score, respectively. These Triage Allocation Scores determine the Triage Category depending on the time of assessment. The comorbidities are listed and summarized with reference labels in Table 1.

At UCLA, the SOFA score was modified (uSOFA) to adequately capture the medical complexity of the patient population at the member hospitals. Specifically, the Cardiovascular component was updated to reflect the use of extracorporeal membrane oxygenation (ECMO), a highly specialized therapy for severe cardiac and/or respiratory failure. All SOFA measures and modifications are included in Appendix B: Various measures of severity of acute illness.

Table 1: Prespecified comorbidities and associated reference labels

Reference Label	Pre-specified Comorbidities
	Major comorbidities that are associated with increased risk of short-term mortality from critical illness
Comorbidity M1	Pre-existing neurological condition (dementia, stroke, other neurodegenerative disease) with baseline modified Rankin Score >= 4
Comorbidity M2	ACC/AHA Stage C heart failure, NYHA Class II-IV
Comorbidity M3	Severe, inoperable multi-vessel coronary artery disease or valvular disease
Comorbidity M4	WHO Class 3 pulmonary hypertension (symptomatic with minimal exertion, asymptomatic only at rest)
Comorbidity M5	Moderately severe chronic lung disease (e.g., COPD, IPF) but not requiring chronic oxygen or ventilation
Comorbidity M6	End-stage renal disease on dialysis
Comorbidity M7	Cirrhosis with MELD < 20 and history of prior decompensation
	Severely life-limiting comorbidities associated with high mortality even in absence of critical illness (survival typically ≤ 1 year), and which are correlated with significantly increased risk of short-term mortality from critical illness
Comorbidity S1	Minimally conscious or unresponsive wakeful state from prior neurological injury
Comorbidity S2	ACC/AHA Stage D heart failure
Comorbidity S3	WHO Class 4 pulmonary hypertension

Reference Label	Pre-specified Comorbidities
Comorbidity S4	Severe chronic lung disease with FEV1 < 20% predicted, FVC < 35% predicted, or in the absences of PFTs, chronic home O2 at rest or mechanical ventilation
Comorbidity S5	Cirrhosis with MELD score ≥ 20
Comorbidity S6	Metastatic cancer with expected survival ≤ 1 year despite treatment OR Refractory hematologic malignancy (resistant or progressive despite conventional initial therapy)
Comorbidity S7	Terminal illness with Clinical Frailty Scale Score ≥ 8

Formation of a Triage Team

The clinical assessment necessary to determine the Triage Allocation Score and Triage Category requires the formation of a Triage Team, a team of clinicians and administrators who review all patients requiring or currently receiving critical care ("critically ill patients") daily. This Team is led by a Triage Officer, who is ideally a physician "with established expertise in the management of critically ill patients." The Policy recommends that this Triage Officer is accompanied by "at least one other licensed health care professional (e.g. nurse and/or respiratory care practitioner) with acute care (e.g., critical care or emergency medicine) experience, and at least one administrative staff member."[13]

Chart Abstraction Protocol

The final key component of the intervention is the protocol for the abstraction of relevant clinical data from the chart, a standardized review of each chart for key clinical information on which each patient's Triage Category is based. The Policy requires a timely, comprehensive review of various pieces of clinical information, including (but not limited to) patient history, bedside nursing assessments, and basic laboratory data to determine the patient's Triage Category. As the medical record is a complex array of information containing multiple data structures, this protocol was designed to streamline the collection and review process, as well as to ensure that patients are evaluated in an equivalent manner.

University of California, Los Angeles and Implementation of the SRAP

The University of California, Los Angeles (UCLA) Health System is a large academic healthcare system that includes four inpatient medical facilities, two of which provide critical care services

to adult patients.[14] Ronald Reagan UCLA Medical Center (RR-UCLA) contains 520 inpatient beds, inclusive of 90 pediatrics beds. While the facility officially reports 120 adult intensive care beds and 13 adult coronary care beds, the health system notes that "each patient room has the capacity to convert into an intensive care unit (ICU) to allow for the continuous care of a critically ill patient in one room."[15] Santa Monica-UCLA Medical Center and Orthopaedic Hospital (SM-UCLA) contains 281 inpatient beds, which includes 22 adult intensive care beds.[16]

Implementation of the SRAP at UCLA Health is achieved through integration into CareConnect, the health system's electronic medical record (EMR) as the Triage Allocation Tool (TAT) to facilitate the collection and communication of data necessary to determine the Triage Allocation Priority Level. The TAT was created in an iterative process by clinicians (including this author) in collaboration with members of the health system's informatics team with input from hospital leadership through virtual meetings that occurred over several months. Through the TAT, aspects of the chart abstraction protocol are automated. For instance, the TAT automatically retrieves the most recent laboratory and flowsheet values necessary to calculate the UCLA modified SOFA score. The Triage Allocation Score and resultant Triage Categories generated by this process are stored in the medical record. Adherence to the SRAP became mandated in the workflow – any patient who requires or is currently receiving critical care must have a Triage Allocation Priority Level determined by the TAT. The Triage Team has unique access to a patient list in the EMR that automatically displays all critically ill patients. The hierarchical nature of the TAT data collection process has implications for the analyses in this dissertation and is visualized in Figure 1.
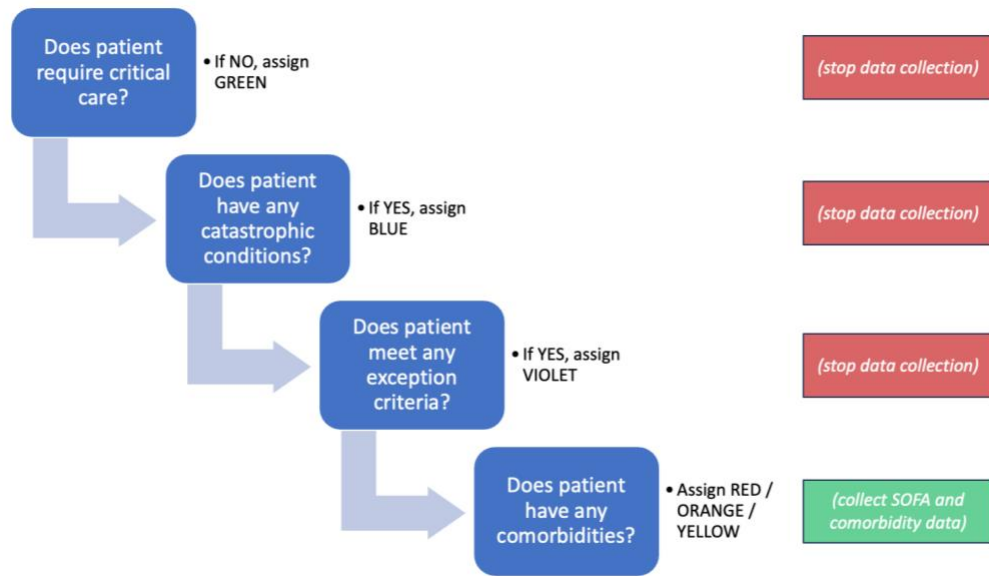
Figure 1: Triage Allocation Tool data collection hierarchy

As part of the organization's ongoing efforts to prepare for the COVID-19 pandemic, investigators at UCLA David Geffen School of Medicine collaborated with UCLA Health hospital leadership to conduct a pilot study implementing the allocation policy through the TAT. For the purposes of the analyses performed in this dissertation, the TAT was used as intended in surge conditions. The study applied to a consecutive cohort of ICU patients admitted to an adult intensive care unit at Ronald Reagan UCLA Medical Center and Santa Monica-UCLA Medical Center between May 26 and August 1, 2021.

As the Policy guides allocation of all adult ICU beds, patients admitted to adult medical, cardiac, surgical, cardiothoracic, and neurological intensive care units were included in these analyses. The Policy examined in this analysis does not explicitly exclude pediatric populations. However, there exists debate in the literature around the ethical issues in allocating resources to, and potentially reallocating resources from, pediatric patients compared to adult patients during crisis standards of care based on the life-cycle principle. In a review of ventilator allocation guidelines at the state level, more than half of the existing policies included separate guidelines for pediatric patients.[17] Some have noted that pediatric patients may need to be

considered separately for logistical issues related to their smaller size that might necessitate different equipment and personnel.[18] While there was no age exclusion criterion for this study, we categorically excluded patients admitted to pediatric intensive care units to address this unsettled issue.

Admission to the ICU occurred according to usual care. First, the clinical team caring for a given patient determined that the patient has developed a need for intensive care. This referring team consulted the ICU team for evaluation, and the ICU team made an independent determination regarding the need for critical care. If the intensivist team agreed that the patient required the ICU for ongoing care, the patient was transferred as soon as a bed was available. If no bed was available, the patient would "board" outside of an intensive care unit, meaning that the patient would be physically housed outside of a unit designated for critical care. In this case, provision of critical care may have been temporarily limited by unit staffing or technical capabilities.

The study consisted of two phases. In the first phase, encompassing the period between May 26, 2021, and June 30, 2021, all eligible patients were scored by two users. The first user, or Primary User, was a clinician previously identified by the organization as a potential member of the Triage Team in the event that the SRAP was enacted for surge conditions. These Primary Users represented three clinical disciplines: physicians, holding a Medical Doctor (MD) or Doctor of Osteopathy (DO) degree; registered nurses in either a clinical or administrative role; or advanced practice providers (APPs) consisting of nurse practitioners (NPs), physician assistants (PAs), or clinical nurse specialists (CNS). The second user, or Investigator, was a clinician member of the pilot study team and consisted of six physicians in pulmonary and critical care medicine or emergency medicine. In the second phase of the study, encompassing the period between July 1, 2021, and August 1, 2021, all eligible patients were scored by a single user, who was a member of either the Primary User or Investigator pools.

For the purposes of the analyses contained in this dissertation, all individual patient data was obtained from CareConnect, the electronic health record at UCLA Health. The Triage Allocation Scores and Categories generated by the Investigators in Phase One of the pilot were calculated in a separate REDCap electronic data capture tool hosted at University of California Los Angeles, based on the same prioritization algorithm underlying the TAT in CareConnect. REDCap (Research Electronic Data Capture) is a secure, web-based software platform designed to support data capture for research studies, providing 1) an intuitive interface for validated data capture; 2) audit trails for tracking data manipulation and export procedures; 3) automated export procedures for seamless data downloads to common statistical packages; and 4) procedures for data integration and interoperability with external sources.[19,20] This study was approved by the Institutional Review Board at the University of California, Los Angeles.

Dissertation Aims

In this dissertation, we aim to address three aspects of the UC SRAP. First, we assess the interrater reliability of the SRAP, hypothesizing that the policy will result in agreement in Triage Category determination. Next, we examine the impact of the SRAP on cohort mortality under varying levels of constraint, hypothesizing that implementation of the SRAP will result in statistically similar mortality under such conditions by allocating resources to those most likely to benefit. Finally, we investigate the mechanisms by which race might play a role in mortality disparities through the SOFA and Comorbidity components of the SRAP.

Chapter 2: Reliability of the Proposed Scarce Resource Allocation Policy in Determination of Prioritization Outcomes

Background and Hypotheses

Given the recent proliferation of resource allocation policies and relative lack of research exploring their usability in real-world settings, our first aim is to describe reliability among raters using the SRAP for resource allocation decision-making as a key implementation metric of the SRAP. As the SRAP is intended to guide determination of critical care allocation priority, it is vitally important that users of the policy agree on the interpretation of its parts. In other words, the Policy must be reliably applied to a given population.

As it is the factor that ultimately determines priority, and therefore reasonably affects a given patient's chance of surviving critical illness in surge conditions, our primary outcome of interest is determination of the Triage Category. Knowing that this primary outcome is, for most patients, dependent on the presence or absence of certain medical comorbidities, our key secondary outcome is determination of the presence of these prespecified comorbidities. Our first hypothesis is that use of the SRAP results in agreement in Triage Category determination as defined by ICC. As a corollary, we hypothesize that the use of the SRAP results in agreement in presence of prespecified comorbidities as defined by ICC.

To our knowledge, this analysis is the first to leverage a commonly used statistic to assess reliability of a resource allocation policy. Intraclass correlation coefficients (ICC) have been proposed as a measure of interrater reliability (IRR) as far back as the late 1970s. Spence Laschinger reviewed and advocated for its use as a measure of IRR in nursing research over other more popular methods at the time, including percentage agreement among raters, Pearson's coefficient, and Cronbach's alpha.[24] Importantly, the author noted that the latter methods are more accurately described as assessments in consistency among raters in scoring

a given observation. In reviewing the use of IRR in analyzing observational data, Hallgren defines reliability as the ratio of the variance in the true measurement of a subject to the variance in the observed measurement.[25] As the variance in the observed measurement is the sum of the variance in the true measurement and the variance in the error measurement, reliability will increase as the variance in the error measurement decreases. In the context of this work, reliability is maximum when the measurement tool, the SRAP, produces consistent ratings independent of user – such that the error variance term approaches zero.

Hallgren further describes several options for determining IRR, including ICC and Cohen's kappa. ICC is a commonly used statistic for ordinal, interval, and ratio variables, and incorporate the magnitude of disagreement in the assessment of IRR such that larger magnitude disagreements result in lower ICC. This is unlike Cohen's kappa, a statistic designed for categorical variables, which relies on all-or-nothing agreement to determine IRR. Also, unlike Cohen's kappa, there are computational variants of ICC that allow the ICC to incorporate the impact of random effects of specific raters on the IRR.

Koo and Li describe in detail ten different versions of the ICC whose applicability varies based on study design, initially described by McGraw and Wong.[26,27] In this overview, the authors outline a method for choosing the appropriate computational variant based on four aspects of the research. The first two aspects – the set of raters and whether these raters are randomly sampled from a larger population or comprise a specific set – determine the "model" selection: one-way random effects, two-way random effects, or two-way mixed-effects. The third aspect – the reliability of a single rater or the mean value of multiple raters – determines the "type" selection: single rater, or mean of k raters, where k is the number of raters to be averaged. The final aspect – concern with agreement or consistency – determines the "definition" selection: absolute agreement or consistency.

As discussed in the introductory chapter, there has been sufficiently documented bias in many of the components of the SRAP among racial and ethnic groups, namely the SOFA score

and certain comorbid conditions. This has led to concern that the use of such criteria in resource allocation policies may systematically disadvantage members of certain racial and ethnic minorities. As the SRAP does not explicitly rely on racial and ethnic group identification for determination of Triage Category, we hypothesize that agreement in Triage Category determination as defined by intraclass correlation coefficient does not differ by racial or ethnic group. Again, as a corollary, we hypothesize that agreement in presence of prespecified comorbidities as defined by intraclass correlation coefficient does not differ significantly by triage allocation level or racial or ethnic group.

Understanding Alternative Measures of Similarity

Given the nature of decision-making required by the SRAP, we explore the application of a select number of other similarity statistics in this analysis. The Jaccard coefficient has been applied to many problem involving vectors of data containing information about the presence or absence of a feature such that for two such sets of data, the Jaccard (or Tanimoto) coefficient is defined as the ratio of their intersection to their union.[29] In terms of the issues discussed here, we propose the Jaccard coefficient as an appropriate measure of similarity for any "yes/no" or "present/absent" determination, which is the case for the pre-specified comorbidities. The Rand index was developed as a method for cluster analysis but has been likewise expanded to problems such as those presented here.[30] The Rand index concerns two sets which are themselves defined as partitioned subsets of a larger set. It defines four types of items in each subset – those that are present in both subsets, those that are absent in both subsets, those that are present in subset 1 and absent in subset 2, and vice versa. In a review of the proliferation of such coefficients and indices to describe similarities between sets, Brusco and colleagues used simulated data sets to show that the Jaccard coefficient and Rand index are highly correlated when the base rate (the rate of "presence", number of "yes" responses) is high in the data set, which is intuitive.[31]

For any "present/absent" determination in our analysis, the difference between the Jaccard coefficient and Rand index can be explained as follows. The Jaccard coefficient answers the question, "for all pairs in the data in which at least one rater determined 'present,' in how many pairs did both raters agree?" In contrast, the Rand index answers the question, "for all pairs in the data, in how many pairs did both raters agree *either* 'present' or 'absent'?" With regards to the comorbidities included in SRAP, policymakers might be more interested in Jaccard coefficient if they are concerned primarily with agreement only when either rater determines the presence of the condition. Alternatively, the Rand index would be more appropriate if the concern is all forms agreement – in this case, both the presence and absence of the condition. The overlap between these similarity measures is shown in Figure 2.

Jaccard coefficient = $\frac{A}{A+B+C}$ Rand index = $\frac{A+D}{A+B+C+D}$		Rater A	
		Yes	No
Rater B	Yes	A	B
	No	C	D

Figure 2: Comparison of Jaccard coefficient and Rand index

Methods

As briefly discussed in Chapter 1, this analysis is based on the pilot study performed at UCLA Health as part of the organization's efforts to prepare for implementation of the SRAP. The study team recruited ninety-seven individuals as potential Triage Team members. Apart from one individual, all members of this group were clinically trained as a physician, registered nurse, and/or advanced practice provider. Excluding the non-clinician, this group formed the pool of Primary Users in assessment of patients admitted to an adult ICU between May 26, 2021, and June 30, 2021. The study team themselves formed the pool of Investigators from which the second rater was chosen. As previously mentioned, the Investigators were all physicians in

either pulmonary and critical care medicine or emergency medicine. The pools were compositionally distinct.

Every day during this period, every patient in each of the six ICUs was scored by one Primary User using the TAT specifically designed for this purpose and previously discussed. All scorers were employed full-time in their roles, such that they performed patient scoring within the confines of their employment schedules. Due to staffing availability, some days had a combination of scorers for a given ICU, but each patient was scored by a single user. The Investigators performed an audit of this process by generating a score for four to five patients for each ICU every day. These numbers were chosen to achieve an audit sample representing fifteen percent of the triage encounters. The Primary User and Investigator were randomly assigned within the constraints of their availability, requested prior to the first day of scoring by the study team and continually updated throughout the study period as needed, with some resultant changes in assignment. In any situation in which the Investigator who was also a member of the Primary Users pool performed primary scoring, another Investigator performed the audit for that ICU on that day. We calculated that with 130 patient encounters scored by a Primary User and Investigator, we can estimate an ICC of 0.9 at an alpha level of 0.05 with a lower bound of 0.86.

Data Collection and Preparation

As previously described in the introductory chapter, REDCap was used to collect and store patient information for the reliability analysis. Five instruments were created to collect information for multiple planned studies – Demographics, Triage Tool Auditor, Triage Team Scores, Care Characteristics, and Social Vulnerability Index (SVI). Data for the present analyses were limited those collected from the first three instruments. Copies of all instruments used are included in Appendix E: Audit instruments used in reliability assessment.

For the audit process, each Investigator was tasked to independently review their assigned patients' charts and input the requested information into REDCap via the Demographics and Triage Tool Auditor instruments. Each Investigator then reviewed the inputs of the Primary Users for each selected patient into the TAT and transcribed those inputs into REDCap via the Triage Team Scores instrument. As can be seen from the examples in the Appendix, the Triage Tool Auditor and Triage Team Scores instruments presented radio buttons for "present," "absent," and "could not determine" for the Investigators to select in assessing for the pre-existing comorbidities. There was no forced selection such that an Investigator could choose to select "absent" or leave all buttons unselected for a given comorbidity. This led to heterogeneity in the expression of absent comorbidities in the downloaded data between 0 when "absent" was chosen and 'NA' when no selection was made. Review of the data entries found records in which the same patient had multiple entries of the Triage Team Scores instrument, with one entry containing 0 for several comorbidities and another entry containing 'NA' for the same comorbidities. This led to the conclusion that no selection was made in cases of absent comorbidities. Additionally, the Policy states that, "in the absence of appropriate expertise … the patient is NOT docked for major comorbidities" – effectively giving patients benefit of the doubt to avoid potential error in lowering priority and withholding or withdrawing resources. Considering these facts, any comorbidity for which no selection was made or for which "could not determine" was selected was recoded as "absent."

Key Variables and Definitions

In this analysis, we define two outcomes to understand agreement in determination of Triage Category. Our outcome of interest for the primary analysis is the Triage Category, which has been previously defined as an ordinal categorical variable with six levels. To allow for ICC calculation for this outcome, the Triage Categories were re-coded as a numerical ordinal variable, with Violet representing the highest priority coded as 6, Red coded as 5, Orange coded

a 4, Yellow coded as 3, Blue coded as 2, and Green coded as 1. The second outcome of interest is the presence of comorbidities. Based on the issues discussed in the Data Collection and Preparation subsection, each of the prespecified comorbidities were coded as 0 for "absent" or 1 for "present."

Based on observations in exploration of the data, we also decided to examine whether there was agreement on indication for ICU level of care, presence of an exemption criterion, or presence of a catastrophic condition. In other words, we determined the ICC specific to the Triage Categories Green, Violet, and Blue, respectively. For these analyses, a new variable was created for each encounter and set to 1 if the rater assigned to the Triage Category of interest and 0 otherwise. Table 2 summarizes the IRR or similarity statistic proposed for each part of the analysis in this chapter.

Table 2: Summary of Outcome Variables and Statistics Used in Analyses

Concern	Variable(s)	Type	Values	Statistic(s)
Agreement in Triage Category determination	Triage Category	Ordinal / Categorical	Violet (6), Red (5), Orange (4), Yellow (3), Blue (2), Green (1)	Two-way random effects ICC, Cohen's kappa
Agreement in presence of ICU indication	Triage Code Green	Binary	1 if Triage Category = Green, 0 otherwise	Jaccard coefficient, Rand index
Agreement in presence of catastrophic condition	Triage Code Blue	Binary	1 if Triage Category = Blue, 0 otherwise	Jaccard coefficient, Rand index
Agreement in presence of exemption criterion	Triage Code Violet	Binary	1 if Triage Category = Violet, 0 otherwise	Jaccard coefficient, Rand index
Agreement in presence of comorbidities	Comorbidities M1-7, S1-7	Binary	1 if comorbidity present, 0 otherwise	Jaccard coefficient, Rand index

Rater background was captured as a categorical variable with three values: 'physician,' 'nurse,' or 'advanced practice provider (APP)'. Each of the comorbidities were also captured as categorical variables, with values of 'present' or 'absent.' To examine the association of difference in rater background with difference in Triage Category determination, we define a new variable "Difference in Triage Category" both as a binary variable, with 0 representing no

difference and 1 representing any difference, and as a multilevel categorical variable in which 0 again represents no difference, but we differentiate cases in which the Investigator assigned a lower priority Triage Category (variable takes on a value of 1) from cases in which the Investigator assigned a lower priority Triage Category (variable takes on a value of 2). The exposure variable, Difference in Rater Background, is a binomial variable which equals 0 if the raters are of the same background and 1 if they are not. A representative schematic of how these variables were analyzed is shown in Figure 3.

Triage Encounter	Rater	Rater Background	Difference in Rater Background	Triage Category	Comorbidity	Difference in Triage Category
	1					
	2					

Figure 3: Structure of data for reliability analyses

Statistical Analysis

The protocolization of the resource allocation process assumes reproducibility of results among a variety of users. By calculating the ICC for both Triage Category and presence of comorbid conditions, we formally assess this assumption with standardized statistical testing.[24]

We examine the distribution of Triage Categories among the groups of Primary Users and Investigators and use pairwise chi-squared testing to determine differences in frequencies between the groups. Finally, we use two-way random effects ICC to define agreement between the two groups to account for a random subset of 2 raters from each pool evaluating n number of patients from the total cohort.[32,33] Conclusions about clinical significance are adopted from guidelines based on review of prior literature, with ICC less than 0.4 indicating poor reliability, ICC between 0.4 and 0.59 indicating fair reliability, ICC between 0.6 and 0.74 indicating good reliability, and ICC 0.75 and greater indicating excellent reliability.[34] We also examine Cohen's kappa to compare conclusions from different testing methods. While the original study was not

designed to detect high IRR within patient subgroups, we calculate the ICC for Triage Category by race in an exploratory manner to identify potential associations of race with reliability.

We repeat this approach using the prespecified comorbidities as the outcome of interest. Since comorbidities were assessed only for patients who were not assigned to the Green, Violet, or Blue Triage Categories, we limited the analyses for this outcome to patients assigned Red, Orange, or Yellow. We examine the rate of detection of comorbidities by Primary Users and Investigators and calculate two-way random effects ICC to define agreement. Given the binary nature of the outcome here, we compare the ICC to the Jaccard and Rand coefficients to compare conclusions from different methods of measuring agreement or similarity. We perform a similar subgroup analysis on Rand coefficients for comorbidities by racial groups to explore if comorbidity agreement differs significantly between these groups.

Finally, we conduct both simple and multinomial logistic regressions of Difference in Triage Category on Difference in Rater background to determine any association between a key rater characteristic and determination of Triage Category. All analyses were conducted in R.[35]

Results

There were 296 total triage encounter scores generated by Primary Users and Investigators for 130 unique patients. There was an asymmetry in the number of encounters scored by each group, reflecting missed encounters in the Primary Users group. Calculation of reliability statistics was limited to encounters scored by both a Primary User and an Investigator, of which there were 139.

Table 3 shows the baseline demographics of the patients represented in all encounters during the study period. The average patient was 61 years old, and the plurality of patients identified as White (43%). 33 percent of patients identified as of Hispanic or Latino ethnicity. The sample was almost evenly split between male and female gender.

Table 3: Demographic information of patients in study sample

Patient Characteristics	N (%)[1]
Total Number of Unique Patients	130
Age (Years), mean [SD]	62 [20]
Race	
White	60 (46%)
Black or African American	14 (11%)
American Indian or Alaska Native	0
Asian	14 (11%)
Native Hawaiian or Other Pacific Islander	1 (0.8%)
Mixed	0
Other	39 (30%)
Decline or Missing	2 (1.5%)
Ethnicity	
Hispanic or Latino	37 (28%)
Not Hispanic or Latino	91 (70%)
Decline or Missing	2 (1.5%)
Gender	
Male	70 (54%)
Female	60 (46%)
Other/Decline	0
Missing	0

[1]Unless otherwise specified

The demographic information for the rater types is shown in Table 4. Investigators were all physicians within critical care, of either Black or White race, majority still in training, and almost evenly split by gender. Primary Users, on the other hand, were majority female, mostly nurses within critical care, majority White or Asian, and had several years' experience.

Table 4: Demographics of raters by type

Demographic	Raters N (%)		
	Primary Users N = 97	**Investigators N= 5**	**All N = 102**
Gender			
Female	68 (70.1%)	2 (40%)	70 (68.6%)
Male	25 (25.8%)	3 (60%)	28 (27.5)
Other	1 (1%)	0	1 (1%)
Missing	3 (3%)	0	3 (2.9%)
Role			
Advanced Practice Provider	3 (3.1%)	0 (0%)	3 (2.9%)
Physician	21 (21.6%)	5 (100%)	26 (25.5%)
Registered Nurse	70 (72.2%)	0	70 (68.6%)
Something else	2 (2.1%)	0	2 (2%)
Missing	1 (1%)	0	1 (1%)
Specialty Group			
Critical Care	94 (96.9%)	5 (100%)	99 (97.1%)
Unknown	3 (3.1%)	0	3 (2.9%)
Race			
American Indian or Alaska Native	1 (1%)	0	6 (5.9%)
Asian	38 (39.2%)	0	42 (41.2%)
Black or African American	4 (4.1%)	2 (40%)	1 (1%)

	Raters N (%)		
Demographic	**Primary Users N = 97**	**Investigators N= 5**	**All N = 102**
White or Caucasian	39 (40.2%)	3 (60%)	38 (37.3%)
Mixed	4 (4.1%)	0	4 (3.9%)
Missing	11 (11.3%)	0	11 (10.8%)
Ethnicity			
Hispanic, Latinx, or Spanish origin	6 (6.2%)	0	6 (5.9%)
Non-Hispanic, Latinx, or Spanish origin	81 (83.5%)	5 (100%)	86 (84.3%)
Prefer not to answer	6 (6.2%)	0	6 (5.9%)
Missing	4 (4.1%)	0	4 (3.9%)
Education			
Academic Doctorate degree	4 (4.1%)	1 (20%)	5 (4.9%)
Associate degree	4 (4.1%)	0	4 (3.9%)
Bachelor's degree	51 (52.6%)	0	51 (50%)
Master's degree	17 (17.5%)	0	17 (16.7%)
Professional School degree	18 (18.6%)	4 (80%)	22 (21.6%)
Missing	3 (3.1%)	0	3 (2.9%)
Years of Training/Experience			
≤2	5 (5.2%)	1 (20%)	6 (5.9%)
3-5	21 (21.6%)	1 (20%)	22 (21.6%)
6-10	16 (16.5%)	0	16 (15.7%)
10-20	33 (34%)	0	33 (32.4%)
≥21	14 (14.4%)	0	14 (13.7%)
I am still in training	5 (5.2%)	3 (60%)	8 (7.8%)
Missing	3 (3.1%)	0	3 (2.9%)

The frequency of Triage Categories by rater type is shown in Table 5 and a histogram demonstrating the distributions for each group is shown in Figure 4. Pairwise chi-squared tests showed that the distributions were significantly different. Primary Users were more likely to determine that a patient had an exemption criterion while Investigators tended to assign higher Triage Categories for patients without exemptions or catastrophic conditions.

Table 5: Frequency of Triage Category by Rater Type

	Outcome	**Number of Patient Encounters** N (%)			**p-value[1]**
	Triage Category	**Primary Users N = 139**	**Investigators N = 139**	**All N = 278**	< 0.001
Need for ICU	Green	8 (5.8%)	5 (3.6%)	13 (4.7%)	
Exemption Criteria	Violet	14 (10%)	4 (2.9%)	18 (6.5%)	
Catastrophic Conditions	Blue	4 (2.9%)	2 (1.4%)	6 (2.2%)	
Acute Illness + Comorbidities	Red	40 (29%)	58 (42%)	98 (35%)	
	Orange	26 (19%)	51 (37%)	77 (28%)	
	Yellow	42 (30%)	16 (12%)	58 (21%)	
	Code Not Calculated / Missing	5 (3.6%)	3 (2.2%)	8 (2.9%)	

[1]Represents results of pairwise Pearson's chi-squared tests between groups
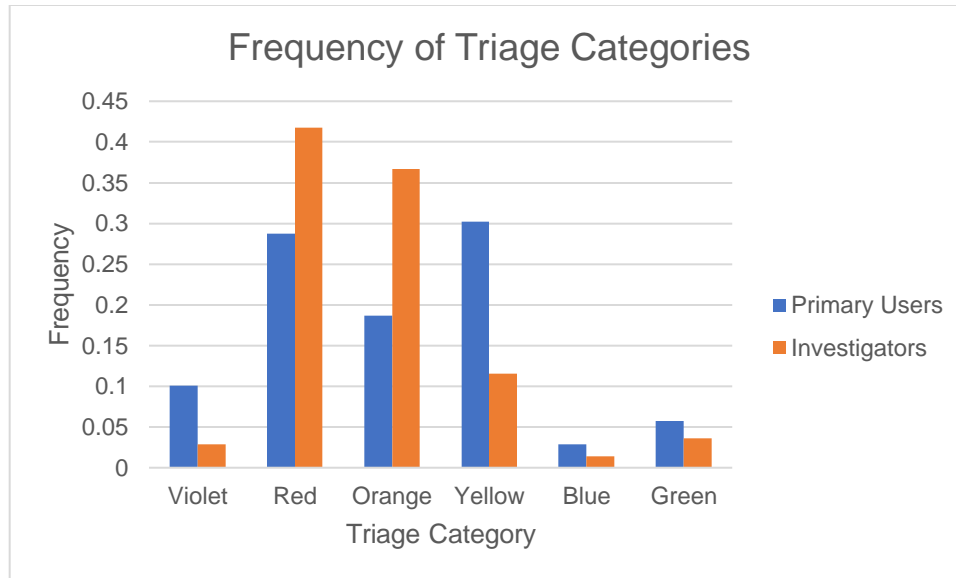
Figure 4: Histogram of Triage Categories by Rater Type

The number of patients in which a given comorbidity was marked present and the corresponding percentage of total patients by rater type is shown in Table 6 and a bar chart depicting detection rates for each rater group is shown in Figure 5. Rates of detection were low across both groups, ranging from 0 to 14 percent. Pairwise chi-squared tests showed that the rate of detection of each of the comorbidities did not differ by rater type.

Table 6: Rate of detection of pre-specified comorbidities by rater type

Outcome	Number of Patient Encounters N (%)			p-value[1]
	Primary Users N = 139	**Investigators N = 139**	**All N = 278**	
Major Comorbidities				
Pre-existing neurological condition (dementia, stroke, other neurodegenerative disease) with baseline modified Rankin Score >= 4	4 (2.9%)	8 (5.8%)	12 (4.3%)	0.4
ACC/AHA Stage C heart failure, NYHA Class II-IV	16 (12%)	18 (13%)	34 (12%)	0.9
Severe, inoperable multi-vessel coronary artery disease or valvular disease	1 (0.7%)	3 (2.2%)	4 (1.4%)	0.6
WHO Class 3 pulmonary hypertension (symptomatic with minimal exertion, asymptomatic only at rest)	5 (3.6%)	6 (4.3%)	11 (4.0%)	> 0.9
Moderately severe chronic lung disease (e.g., COPD, IPF) but not requiring chronic oxygen or ventilation	1 (0.7%)	3 (2.2%)	4 (1.4%)	0.6
End-stage renal disease on dialysis	14 (10%)	14 (10%)	28 (10%)	> 0.9
Cirrhosis with MELD < 20 and history of prior decompensation	4 (2.9%)	4 (2.9%)	8 (2.9%)	> 0.9
Severely Life-Limiting Comorbidities				

Outcome	Number of Patient Encounters N (%)			p-value[1]
	Primary Users N = 139	Investigators N = 139	All N = 278	
Minimally conscious or unresponsive wakeful state from prior neurological injury	0	0	0	N/A
ACC/AHA Stage D heart failure	12 (8.6%)	14 (10%)	26 (9.4%)	0.8
WHO Class 4 pulmonary hypertension	6 (4.3%)	6 (4.3%)	12 (4.3%)	> 0.9
Severe chronic lung disease with $FEV_1 < 20\%$ predicted, FVC < 35% predicted, or in the absences of PFTs, chronic home O_2 at rest or mechanical ventilation	19 (14%)	19 (14%)	38 (14%)	> 0.9
Cirrhosis with MELD score ≥ 20	14 (10%)	13 (9.4%)	27 (9.7%)	> 0.9
Metastatic cancer with expected survival ≤ 1 year despite treatment OR refractory hematologic malignancy (resistant or progressive despite conventional initial therapy)	4 (2.9%)	4 (2.9%)	8 (2.9%)	> 0.9
Terminal illness with Clinical Frailty Scale Score ≥ 8	0	2 (1.4%)	2 (0.7%)	0.5
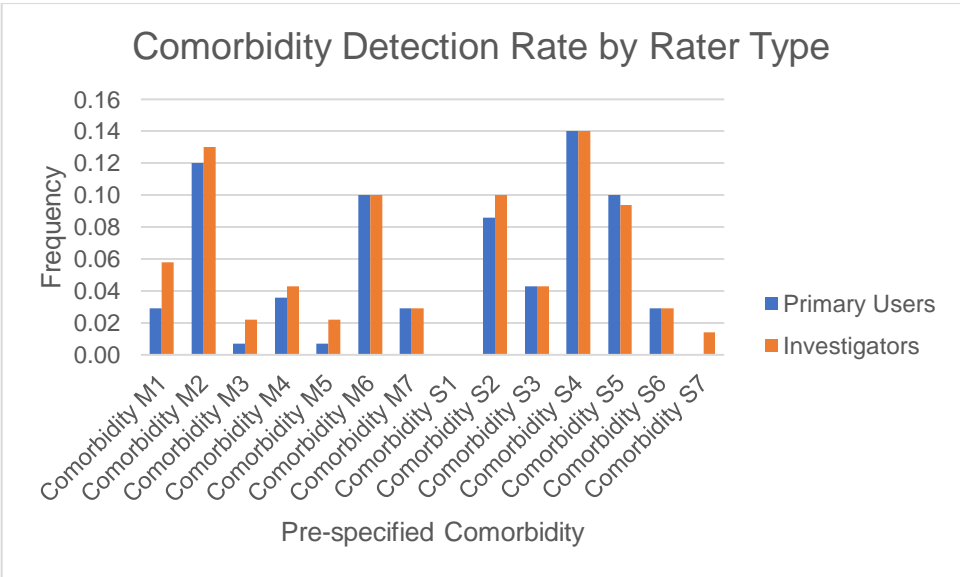
Figure 5: Bar Chart of Comorbidity Detection Rate by Rater Type

Results for the primary analysis are shown in Table 7. The ICC for Triage Category was 0.37, indicating poor reliability. While the study was not powered to determine excellent reliability for the three levels shown, these are included as an exploratory analysis given the results from the main analysis. Table 8 shows the IRR as measured by the ICC and Cohen's kappa for the Triage Category outcome. While conclusions about statistical significance cannot be drawn about the difference between the measurements, the data suggest that agreement is similar as assessed by the two measurements.

23

Table 7: Intraclass correlation coefficients for all Triage Categories and special populations

Triage Category	Intraclass Correlation Coefficient (ICC)	
	Estimate	95% CI (Lower, Upper)
All	0.37	0.22, 0.50
Green	0.50	0.37, 0.62
Blue	0.31	0.16, 0.46
Violet	0.33	0.18, 0.47

Table 8: Interrater reliability measures for Triage Category

IRR Measurement	Estimate	95% CI (Lower, Upper)
ICC	0.37	0.22, 0.50
Cohen's Kappa	0.32	0.21, 0.42

Results for the subgroup analysis of interrater reliability by patient racial group are shown in Table 9. While conclusions about statistical significance cannot be drawn with regards to the differences in these estimates, these point estimates range from poor to good reliability.

Table 9: Intraclass correlation coefficients for Triage Category by patient racial group

Race	N[1]	Interrater Reliability for Triage Category	
		ICC	95% CI (Lower, Upper)
White	58	0.33	0.08, 0.63
Asian	14	0.64	0.21, 0.53
Black or African American	15	0.24	0, 0.65
Native Hawaiian or Other Pacific Islander	2	0	0, 0.99
Other	49	0.40	0.13, 0.61

[1]Represents number of matched observations per rater type such that 2N is total number of observations included in analysis

Interrater reliability and similarity statistics for each of the pre-specified comorbidities identified for assessment in the SRAP are shown in Table 10 and Table 11.

Table 10: Intraclass correlation coefficients for all pre-specified comorbidities

Outcome	Intraclass Correlation Coefficient (ICC)	
	Estimate	95% CI (Lower, Upper)
Major Comorbidities		
Pre-existing neurological condition (dementia, stroke, other neurodegenerative disease) with baseline modified Rankin Score >= 4	0.66	0.55, 0.74
ACC/AHA Stage C heart failure, NYHA Class II-IV	0.47	0.33, 0.59
Severe, inoperable multi-vessel coronary artery disease or valvular disease	0.50	0.36, 0.61
WHO Class 3 pulmonary hypertension (symptomatic with minimal exertion, asymptomatic only at rest)	0.72	0.63, 0.79
Moderately severe chronic lung disease (e.g., COPD, IPF) but not requiring chronic oxygen or ventilation	0	0, 0.17
End-stage renal disease on dialysis	0.76	0.68, 0.82
Cirrhosis with MELD < 20 and history of prior decompensation	0.83	0.77, 0.88
Severely Life-Limiting Comorbidities		
Minimally conscious or unresponsive wakeful state from prior neurological injury	N/A	N/A

24

	Intraclass Correlation Coefficient (ICC)	
Outcome	Estimate	95% CI (Lower, Upper)
ACC/AHA Stage D heart failure	0.75	0.66, 0.81
WHO Class 4 pulmonary hypertension	0.90	0.86, 0.93
Severe chronic lung disease with $FEV_1 < 20\%$ predicted, FVC < 35% predicted, or in the absences of PFTs, chronic home O_2 at rest or mechanical ventilation	0.58	0.45, 0.68
Cirrhosis with MELD score ≥ 20	0.88	0.83, 0.91
Metastatic cancer with expected survival ≤ 1 year despite treatment OR refractory hematologic malignancy (resistant or progressive despite conventional initial therapy)	0.74	0.66, 0;81
Terminal illness with Clinical Frailty Scale Score ≥ 8	0	-0.16, 0.16

Table 11: Alternative similarity statistics for all pre-specified comorbidities

	Similarity Statistic	
Outcome	Jaccard Coefficient	Rand Index
Major Comorbidities		
Pre-existing neurological condition (dementia, stroke, other neurodegenerative disease) with baseline modified Rankin Score >= 4	0.5	0.96
ACC/AHA Stage C heart failure, NYHA Class II-IV	0.36	0.77
Severe, inoperable multi-vessel coronary artery disease or valvular disease	0.33	0.98
WHO Class 3 pulmonary hypertension (symptomatic with minimal exertion, asymptomatic only at rest)	0.57	0.94
Moderately severe chronic lung disease (e.g., COPD, IPF) but not requiring chronic oxygen or ventilation	0	0.93
End-stage renal disease on dialysis	0.64	0.89
Cirrhosis with MELD < 20 and history of prior decompensation	0.6	0.96
Severely Life-Limiting Comorbidities		
Minimally conscious or unresponsive wakeful state from prior neurological injury	N/A	1
ACC/AHA Stage D heart failure	0.63	0.91
WHO Class 4 pulmonary hypertension	0.71	0.98
Severe chronic lung disease with $FEV_1 < 20\%$ predicted, FVC < 35% predicted, or in the absences of PFTs, chronic home O_2 at rest or mechanical ventilation	0.46	0.80
Cirrhosis with MELD score ≥ 20	0.8	0.94
Metastatic cancer with expected survival ≤ 1 year despite treatment OR refractory hematologic malignancy (resistant or progressive despite conventional initial therapy)	0.6	0.98
Terminal illness with Clinical Frailty Scale Score ≥ 8	0	0.98

The Rand index reflecting assessment similarities for each pre-specified comorbidity by patient racial group are shown in Table 12.

Table 12: Rand index for all pre-specified comorbidities by patient race

	Rand Index				
Outcome	White	Asian	Black	NHPI	Other
Major Comorbidities					

Outcome	Rand Index				
	White	Asian	Black	NHPI	Other
Pre-existing neurological condition (dementia, stroke, other neurodegenerative disease) with baseline modified Rankin Score >= 4	0.95	1	0.82	1	1
ACC/AHA Stage C heart failure, NYHA Class II-IV	0.74	0.82	1	1	0.71
Severe, inoperable multi-vessel coronary artery disease or valvular disease	0.95	1	1	1	1
WHO Class 3 pulmonary hypertension (symptomatic with minimal exertion, asymptomatic only at rest)	0.90	1	1	1	0.95
Moderately severe chronic lung disease (e.g., COPD, IPF) but not requiring chronic oxygen or ventilation	0.95	0.82	1	1	0.90
End-stage renal disease on dialysis	0.90	1	1	1	0.82
Cirrhosis with MELD < 20 and history of prior decompensation	0.95	1	1	1	0.95
Severely Life-Limiting Comorbidities					
Minimally conscious or unresponsive wakeful state from prior neurological injury	1	1	1	1	1
ACC/AHA Stage D heart failure	0.82	1	1	1	0.95
WHO Class 4 pulmonary hypertension	0.95	1	1	1	1
Severe chronic lung disease with FEV_1 < 20% predicted, FVC < 35% predicted, or in the absences of PFTs, chronic home O_2 at rest or mechanical ventilation	0.90	0.67	0.82	1	0.71
Cirrhosis with MELD score ≥ 20	0.90	0.82	1	1	1
Metastatic cancer with expected survival ≤ 1 year despite treatment OR refractory hematologic malignancy (resistant or progressive despite conventional initial therapy)	1	1	1	1	0.95
Terminal illness with Clinical Frailty Scale Score ≥ 8	0.95	1	1	1	1

Results for simple and multinomial logistic regressions are shown in Table 13 and Table 14, respectively.

Table 13: Logistic Regression Results for Difference in Rater Background and Any Difference in Triage Category

	Coefficient	p-value
Intercept	1.3041	< 0.001
Difference in Rater Background	-0.7062	0.121

[1]Represents results of Wald test at α = 0.05, less than or equal to 0.05 considered significant

Table 14: Logistic Regression Results for Difference in Rater Background and Difference in Triage Category Determination

	No Difference	Investigator Lower		Investigator Higher	
		Coefficient	p-value[1]	Coefficient	p-value[1]
Intercept	Reference	0.4568	0.119	0.7444	0.007
Difference in Rater Background		-0.6574	0.220	-0.7444	0.143

[1]Represents results of Wald test at α = 0.05, less than or equal to 0.05 considered significant

Discussion

Determining Triage Category and Presence of Comorbidities

The results of this study suggest overall that the SRAP demonstrates poor reliability in guiding

determination of resource allocation priority. This is first evident in the distribution of Triage

Categories as visualized in Figure 4. The p-value of less than 0.001 from the Omnibus test for

differences in any of the ratings further suggests that these distributions are significantly

different and that the two groups in the study differently determined Triage Category for a given

patient. The similarity between the ICC and Cohen's kappa calculations further supports the

conclusions drawn. The study was not powered to detect differences in ICC in race subgroup

analyses, and extreme caution should be taken in interpreting any such results given the small

number of observations in most of the groups. However, the large range of the estimates

encompassing the five subgroups (0 to 0.64) is worthy of attention in future studies.

While the policy demonstrated poor reliability in determination of Triage Category, the

results for the pre-specified comorbidities were more promising. The exploratory comparison of

detection rates across comorbidities argues against this being a likely cause of differences in

Triage Category determination and is supported by the subsequent analyses. Even the ICC

values, arguably the least accurate statistic for measuring similarity in these cases, are

noticeably higher for the comorbidities than for the Triage Category. The Jaccard coefficients

and Rand indices for each comorbidity are lower and higher, respectively, than the ICC. This is

likely because the Jaccard coefficient systematically ignores all cases in which both raters

determined that a comorbidity was absent, removing the same quantity from both the numerator

and denominator of the measure thereby reducing the value compared to the Rand index.

Given primary concern for agreement, as opposed to accuracy, we did not define a "gold

standard" measurement. In doing so, we suggest that establishing agreement if sufficient to

support policy use, but it should be noted that raters might agree on the "wrong" allocation

27

decision. It is a separate but worthwhile question to ask how well a random group of raters might correctly determine allocation priority according to an identified standard.

Choosing the Appropriate Similarity Measure

With regards to which measure is more appropriate, this is dependent on whether negative or absence matches are of importance to the policy implementers. One might argue that focusing on positive matches, those in which both raters agree that a comorbidity is present, allows the policymakers to emphasize reliability in the aspects of the policy that systematically lower a patient's priority for resources, recalling that the presence of any comorbidity adds at least two points to the Triage Allocation Score, potentially lowering the Triage Category. In this case, the Jaccard coefficient would be the appropriate measure of reliability. On the other hand, one could argue that both positive and negative matches are important because the combination of these represent pure agreement – regardless of direction. Agreeing on absence of a comorbidity gives a patient a relative advantage in the prioritization process, so it seems reasonable to determine whether raters agree that this advantage should be conferred. In this case, the Rand index is more appropriate.

Relationship between Rater Background and Reliability

Finally, the results of the logistic regression further suggest poor reliability in determination of the primary outcome, Triage Category. Turning to the results shown in Table 13, the probability of a difference in Triage Category is quite high at baseline, which in the context of this analysis refers to no difference in rater background and is represented by the intercept in the regression. This intercept, which was statistically significant, corresponds to an odds ratio of 3.68, which translates to a probability of 78.6 percent that two physicians would assign a different Triage Category to a given patient. This high probability of disagreement among two raters of the same background is particularly concerning when compared to the probability of disagreement given random chance. With six Triage Categories for each rater to choose from, there exists 36

possible combinations of Triage Categories. There are six combinations that represent

agreement in Triage Category, and thus the probability that the raters agree is $\frac{6}{36}$ or 16.7

percent. The probability of disagreement is then 1 minus this value, or 83.3 percent, which falls

within the 95% confidence interval of the probability estimate from the logistic regression. This

analysis suggests that the use of the SRAP does not significantly improve the probability of

disagreement among two raters of the same background compared to chance alone.

While the p-value for the coefficient for difference in rater background did not meet

criteria for statistical significance, the results are perplexing in that the negative coefficient

suggests that a difference in rater background reduces the likelihood of a difference in Triage

Category determination. In this case, the odds ratio for difference in rater background is 1.82,

which corresponds to a 64.5 percent probability in difference in Triage Category determination

when the raters come from different professional backgrounds.

Implications

This analysis is the first work to our knowledge to examine the reliability of a resource allocation

policy among a trained group of users in deciding allocation priority. Furthermore, this work

analyses a key component of an allocation policy in determination of this priority as well as

patient and rater factors that might influence these determinations. The study was designed to

detect high interrater reliability with adequate power. In addition, our study considers multiple

measures of reliability that might be of interest in the application of such policies. While ICC is

an appropriate measure for the Triage Category outcome, the robustness of the estimate is

supported by similar results in the calculation of Cohen's kappa. The data supporting the study

was largely complete and missingness was negligible in the variables and outcomes of interest.

With regards to reliable assessment of the Comorbidities, our analyses highlight the

importance of defining reliability. While the Jaccard coefficient is commonly used to assess

similarity in binary traits, its definition ignores the agreement in the absence of such traits. The

Rand index, on the other hand, measures agreement in both the absence and presence of such traits. In this sense, the Rand index may be more informative in the assessment of reliability for our purposes. This is particularly compelling in the assessment of the SRAP's prespecified comorbidities. In the example of Comorbidity M5, the Jaccard coefficient communicates that there is no agreement among raters in the presence of "moderately severe chronic lung disease (e.g., COPD, IPF) but not requiring chronic oxygen or ventilation." Reasons for such poor agreement could be that the SRAP does not more explicitly define the parameters needed to mark the Comorbidity as "present," thus leaving room for variable interpretation. The Rand index of 0.94 for the same Comorbidity, on the other hand, would suggest that users mostly agree on whether this Comorbidity is present or absent in each patient. These seemingly incongruent results are explained by the fact that there are no positive matches for Comorbidity M5 and only four of the 139 observations represent mismatches, such that the high Rand index is driven by agreement in the absence of Comorbidity M5. Low Jaccard coefficients might support the notion that poor agreement among the Comorbidities impacts the overall agreement in Triage Category. However, the high Rand indices, reflecting agreement among users regarding both the presence and absence of the Comorbidities, suggest that they are less likely to explain the overall poor reliability of the SRAP in determining Triage Category.

Limitations

Regarding threats to validity, this study has a few limitations. In the initial design, the Investigator group, who served as auditors, was limited in size and variety as compared to the Primary Users. There was no variation in role, and several raters in this group were still in training at the time of the study. This small size limits the external validity of our findings as it is possible that the distribution of ratings in the Investigator pool is due to individual raters in this pool rather than due to true differences in application of the SRAP. Additionally, the homogeneous nature of the Investigator group constrains our conclusions about the impact of

rater background on Triage Category determination to physician-non-physician comparisons. With regards to type of clinical experience, there was minimal representation of non-critical care backgrounds among all raters. While this is likely desirable by those implementing the policy (and to an extent explicitly called for by the policy), this limits the ability to assess the impact of critical care experience on differences in Triage Category determination. From the author's experience as a study participant, we know that different clinical roles are presented with user interfaces in the EMR unique to those roles, which may have impacted the accessibility of information necessary for the Triage Category determination. Additionally, certain providers are more likely to access certain types of clinical information more regularly – for example, physicians are more likely to know where to find pulmonary function testing data, which is necessary for determining the presence of Comorbidity S4. Such differences in workflow may have consequently affected reliability assessments.

As mentioned in the Data Collection and Preparation section, the instruments used led to heterogenous expression of "absent" comorbidities, which we handled by coding all non-responses as "absent." While this could in theory lead to inaccurate analysis of the data, this is such recoding is unlikely to misrepresent the actual conclusions drawn by the raters, as we would expect that detection of any individual comorbidity would be marked as "present."

In our study, the SRAP was operationally implemented via the TAT in the electronic medical record. While this greatly facilitated data collection and determination of Triage Category for allocation purposes, the use of the TAT is, to our knowledge, available only in our institution and thus limits the ability to replicate this experiment in other study settings. Moreover, our study does not allow us to assess how the automation of the process via the TAT impacts the reliability of the SRAP, but one would suspect that such automation would reduce random user error and improve reliability.

The following chapter focuses on expected mortality outcomes as a function of the prioritization decisions guided by the SRAP using simulation methods.

Chapter 3: Evaluating the Impact of the Scarce Resource Allocation Policy on Population Mortality Using Simulation Methods

Background and Hypotheses

Resource Allocation Policies in Societal Context

The SEIR model, a popular framework in epidemiology was first described in 1927 as a mathematical model to better understand the spread of diseases.[21] The model commonly divides a given population into four stages: susceptible, exposed (not included in the original description), infected, and recovered. More recently, this model has been foundational to understand the spread of COVID-19 in varying distinct populations around the world. Inthamoussou and colleagues extended the framework in a simulation analysis to provide data to Argentinian policymakers in decisions around vaccination and reopening policies.[22] Shin modified the model to incorporate death rates and used it in a multi-stage process to more accurately predict the progress of the pandemic in Korea.[23]

As the UC SRAP strictly dictates the allocation of critical care resources within a hospital setting, its scope can be considered limited to the space between the "infected" stage, representing those individuals who require hospitalization and evaluation for critical care resources, and the "recovered" stage. Some individuals may not require hospitalization and thus may not be at all affected by implementation of this policy. This concept is visually described in Figure 6. The inset diagram provides the framework for the simulation-based analysis of the UC SRAP that is described in this chapter.
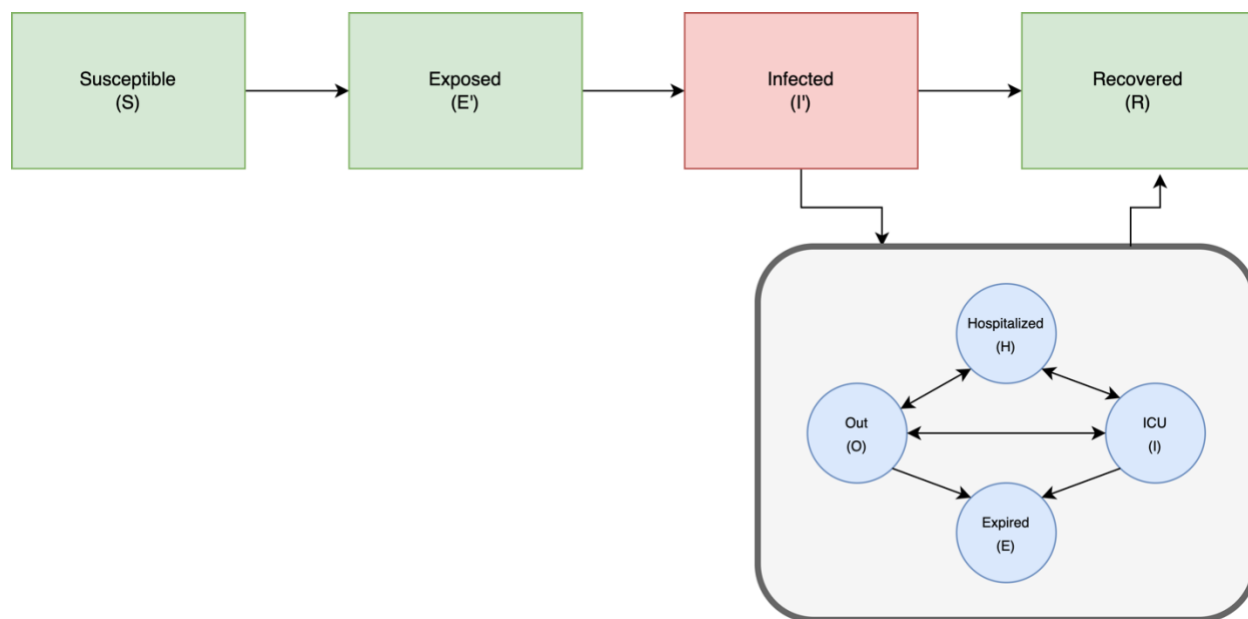
Figure 6: Modified SEIR framework contextualizing role of resource allocation policies

Simulation in Scarce Resource Allocation

A challenge in designing studies on the impact of resource allocation policies on population

outcomes is their implementation. A trial of the policy would require enacting a proposed policy

in one setting while continuing standard practice in another setting with similar resources and

patients. An alternative design is recording outcomes prior to implementation for a determined

period, followed by an observation of outcomes under implementation of the policy, followed

again by a period of observation with de-implementation of the policy, in an ABA design. These

designs have ethical as well as practical considerations. Simulation methods offer a practical

investigative solution to a complex clinical and operational problem.

Kreke and colleagues encourage expanded use of simulation modeling in critical care,

with a focus on three types of simulation methods.[36] Simulated decision models in critical care

have relied heavily on *state-transition cohort models*, such as Markov models.[36] These models

have some applicability in critical care but require limiting assumptions about transitions through

future states, namely that such transitions do not depend on prior states. Additionally, Markov

models are cohort-oriented and do not allow the simulator to incorporate attributes to specific to

33

the individuals in the cohort in the analysis of outcomes. *Discrete-event simulation* includes individual attributes for more robust modeling. This involves greater data requirements and increased computational time and increases the risk of model overspecification.[37]

Existing simulation studies lack the richness or responsiveness to the question posed in this study. Recent simulation studies examining resource allocation policies on outcomes in critically ill patients have been concerned with a limited scope of critical care resources (e.g., ventilators) or patient populations (e.g., patients diagnosed with COVID-19) or lacked real-world data to compare with model output. Most have used Monte Carlo simulation which limits the generalizability of their findings.

For example, Bhavani and colleagues recently studied four distinct ventilator allocation protocols among critically ill patients with COVID-19, using Monte Carlo methods to simulate reduction in ventilator capacity by 50 percent and recording allocation to the patient with a higher priority score under each protocol based on static data. Their conclusions about the impact of these policies are limited by the population of interest, the lack of standardized indications for mechanical ventilation, and the inability to account for the evolving illness history for individual patients that might lead to dynamic changes in allocation priority.[38]In a more recent publication evaluating the impact of implementation of the proposed resource allocation policy in the state of Massachusetts, Riviello et. al. examine the expected outcomes from policy implementation on expected mortality and racial disparities from a retrospective cohort of patients from six Boston hospitals.[39] Similar to the UC SRAP, the Massachusetts guidelines use a multi-principle strategy based on SOFA scores and assessments of comorbidities, although operationalization of the latter component was modified in April 2020 to reflect assessment of near-term mortality (five years versus one year).[40] Their analysis included only patients for whom priority scores were completed during their admission, limiting their ability to reliably assess the impact of the proposed policy. Unlike the Bhavani study, their analysis included all patients admitted to the ICU, but again, their resource allocation concern was limited to

mechanical ventilation. Finally, their method for simulating resource constraint assumed availability of resources for all patients within a priority group, as they chose to constrain by simulating allocation of ventilator to all patients above a priority score threshold and to no patients below that threshold. This more closely resembles a Markov model, considering cohorts within a cohort, which prevents experimental handling of the possibility that patients of equal priority may compete for limited resources.

Microsimulation leverages the state-based transition modeling of Markov models but relaxes the limiting assumptions and simulates individual trajectories for patient cohorts to more accurately assess the impacts of policies and interventions on heterogenous populations.[41] Krijkamp and colleagues modified the Sick-Sicker model (Figure 7), originally proposed by Enns and colleagues, to build a microsimulation model to understand cost-effectiveness related to treatment of a disease.[41,42] In the figure, the circles represent transition states, the collectively exhaustive set of conditions representing patients in the system, and the arrows represent transition probabilities, the probability that patients transition from one state to another.
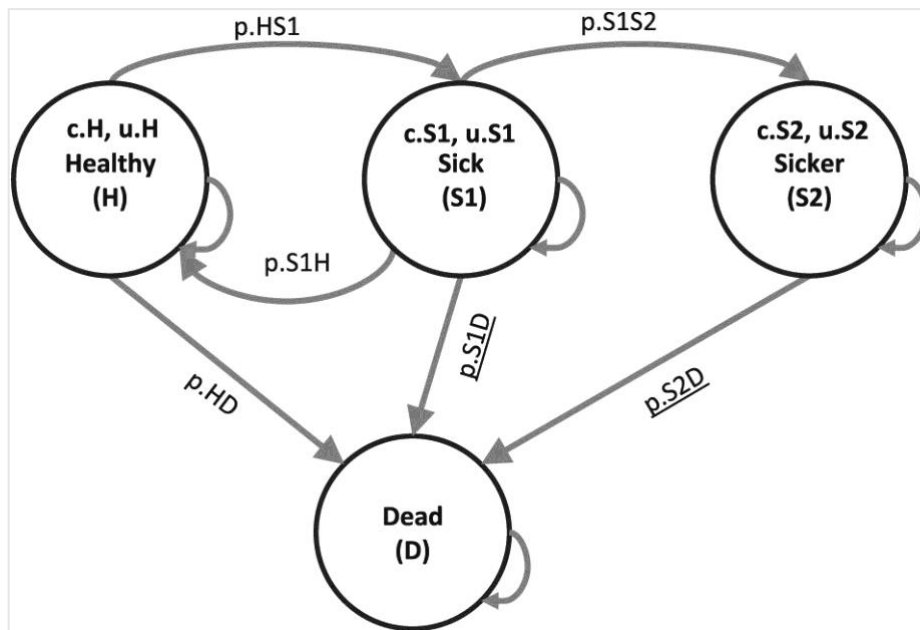
Figure 7: Sick-Sicker simulation model modified by Krijkamp et. al.

Krijkamp and colleagues use microsimulation (as an intermediary in calculating a cost-effectiveness value) to understand individual and cohort outcomes with determined transition probabilities. Microsimulation models define mutually exclusive and exhaustive transition states – in other words, the transition states in the model are the only states in which patients can exist, and patients can only occupy one state at a time. The transition state model used in our microsimulation, based on the microsimulation used by Krijkamp and colleagues, is shown in Figure 7, and the definitions of each transition state are summarized in Table 17.
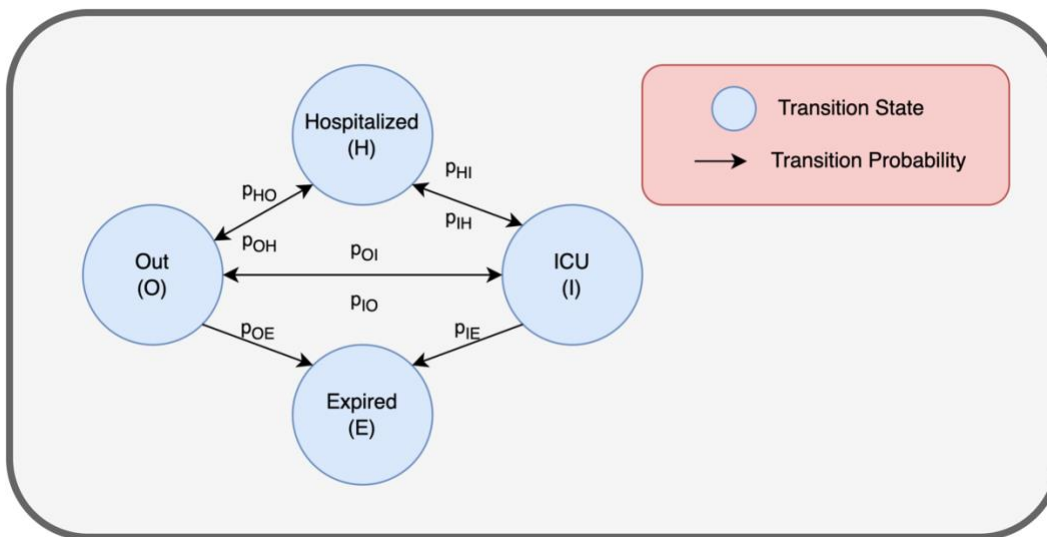
Figure 8: Microsimulation states

In evaluating the implementation of resource allocation policies such as the SRAP, researchers acknowledge that the transition probabilities are not known *a priori*. The microsimulation model offers a framework by which we might understand how these transition probabilities, which represent likelihood of resource allocation or mortality from withholding of resources, vary by patient or policy factors.

Conceptual Framework

The SRAP aims to maximize lives saved by allocating critical care resources using an algorithm to identify patients who are most likely to benefit from such resource allocation. A proposed framework depicting the relationship between the Policy, the allocation outcome, and mortality is

shown in Figure 9. This framework incorporates Patient Characteristics as possible co-variates in the model (denoted by the dashed arrow).
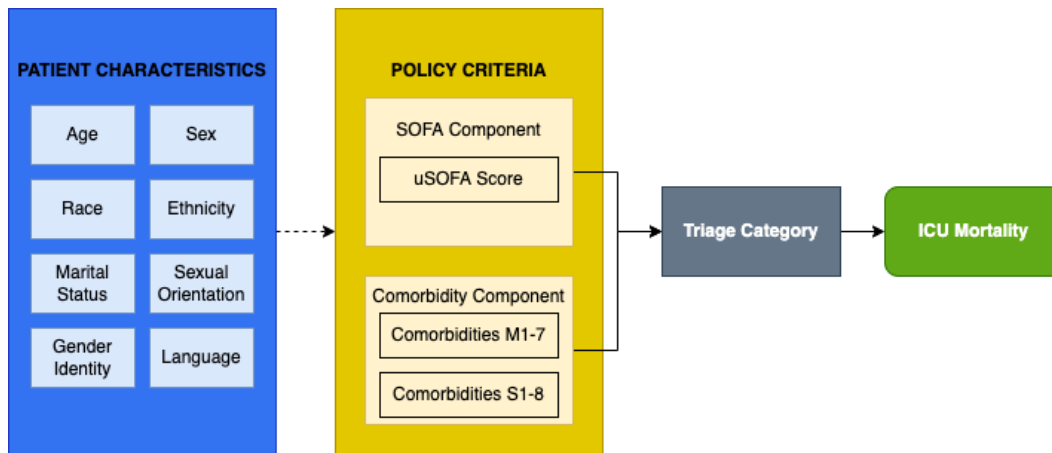
Figure 9: Conceptual framework relating SRAP to ICU mortality

Methods

Data Collection and Preparation

The data for this study was obtained from the institution's electronic health record. The population of interest included all patients aged 18 years and older admitted to an adult ICU between May 26 and August 1, 2021. Data types included patient demographics, patient identifiers, encounter information, hospital unit information, encounter diagnoses, procedures completed, problem lists, vital signs and other flowsheet data, laboratory test results, medication orders or administration, and social history. A more detailed description of these data can be found in Appendix F: Medical Record Data Fields and Dictionary.

In the study, each ICU was assigned a Triage Officer to complete scoring for every patient in the unit (Chapter 2 describes this method). Team members were encouraged to complete the scoring early in the day although the demands of clinical duties resulted in scoring taking place throughout the day.

The Patient Demographics, Patient Identifiers, and Triage Allocation flowsheets were merged by the unique 'IP_Patient_ID' variable. Patients were re-scored every 72 hours except

in the event of resolved need for ICU, development of an exemption, or development of a catastrophic condition. As such, during the data collection, many patients were in an ICU and had study days without a Triage Category filed. Any patient who did not meet the exceptions previously stated was assumed to have the same Triage Category, effectively carrying forward the most recent Triage Category determination until the next known value as shown in Figure 10. This resulted in a master dataset of 3773 triage encounters for 974 unique patients over 68 study days. We excluded any patient for whom a Triage Category could not be determined at any time during the study. This resulted in a simulation dataset of 3626 triage encounters for 963 unique patients as shown in Figure 11.
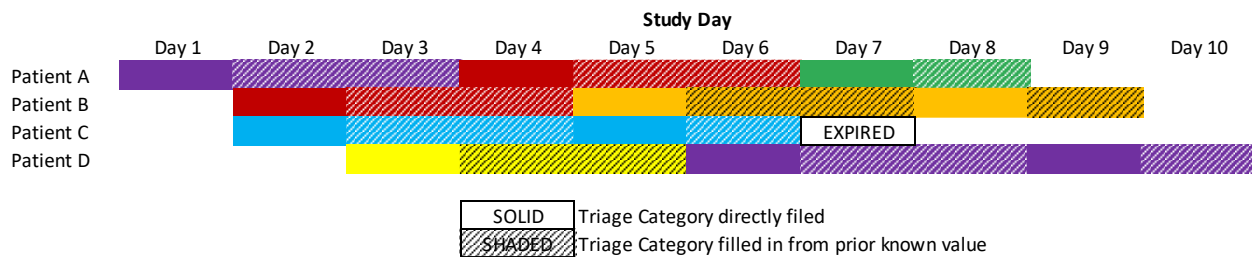
Figure 10: Diagram showing triage category data completion for sample ICU patients
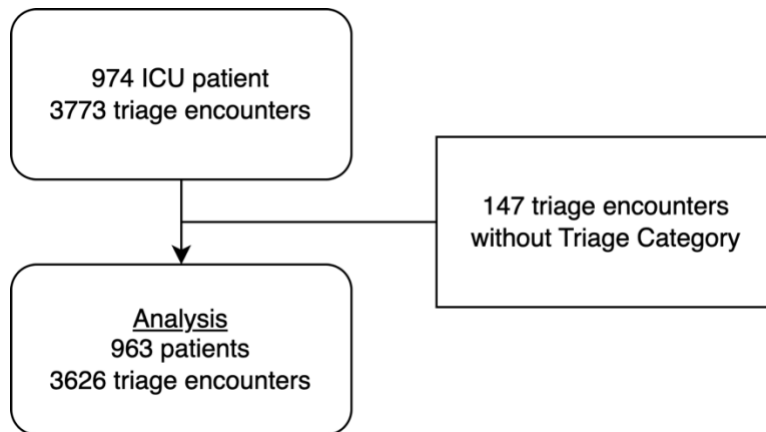
Figure 11: Inclusion and exclusion diagram for microsimulation study cohort

Key Variables and Definitions

The simulation examines how mortality is impacted by the level of constraint on critical care resources. We tested two definitions of cohort mortality. In one model, cohort mortality is

represented by the *expired fraction*, a continuous variable between 0 and 1, measuring the fraction of times in the simulation that a patient expires. In another model, cohort mortality is represented by the *expired count*, a count variable measuring the number of times that a patient expires in the simulation.

Patient Characteristics are demographic variables that were available in the medical record. These include *age*, a continuous integer variable; *sex*, a binary categorical variable; and *race*, *ethnicity*, *marital status*, *sexual orientation*, *gender identity*, and *language*, all categorical variables. Variable values were defined from the unique values extracted from those fields in the medical record. *Race*, *ethnicity*, *marital status*, *sexual orientation*, *gender identity*, and *language* were recoded to facilitate interpretation of analyses.

Policy Criteria include illness severity and comorbidity. The "objective measure of acute illness severity" is summarized by the SOFA Component, which is determined by the uSOFA score at the time of evaluation. SOFA Points takes on an integer value between 1 and 4. The "co-occurring conditions that moderate mortality" are summarized by the Comorbidity Component, which is determined by the presence of one or more prespecified comorbidities. Comorbidity Component takes on a value of 0, 2, 4, or Unknown/Unavailable. All variables, their recoded values, and their relationships to each other are summarized in Table 15.

Table 15: Summary of Exposure and Outcome Variables

	Variable	Type	Values
Outcome	*Mortality*		
	Expired fraction	Continuous	0 – 1
	Expired count	Count	1 – 1000
Exposure	*Patient Characteristic*		
	Age	Continuous	
	Sex	Binary Categorical	Female, Male
	Race	Categorical	White or Caucasian, Black of African American, Asian, Native Hawaiian or Other Pacific Islander, Middle Eastern or North African, American Indian or Alaska Native, Do Not Identify, Other, Unknown
	Ethnicity	Categorical	Hispanic/Latino, Not Hispanic Latino, Other, Unknown
	Marital Status*	Categorical	Partnered, Not Partnered, Unknown
	Sexual Orientation*	Categorical	Straight, Lesbian or Gay, Bisexual, Other, Unknown

	Variable	Type	Values
	Gender Identity*	Categorical	Male, Female, Transgender Male, Unknown
	Language	Categorical	English, Non-English, Unknown
	Policy Criteria		
	SOFA Component	Integer	1 – 4
	uSOFA score	Integer	0 – 24
	Comorbidity Component	Nominal	0, 2 (if any present from Comorbidities M1-7), 4 (if any present from Comorbidities S1-8), Unknown/Unavailable
	Comorbidities M1-7	Binary	0 (Absent), 1 (Present)
	Comorbidities S1-8	Binary	0 (Absent), 1 (Present)

*Represents data included in the medical record but excluded from regression models

Simulation Methods

Our microsimulation model simulates the policy effects by constraining the number of ICU beds that are available daily. Policymakers might think in terms of constraints or in terms of excess demand. The constraint levels and the excess demand that the constraints are equivalent to in the simulation are described in Table 16. We apply the Policy in the model by allocating ICU beds as the policy dictates and recording these allocations as outcomes.

Table 16: Simulation Scenarios

Constraint Level	Bed Reduction	Excess Demand
Base	None	None
Moderate	50%	2-fold increase in patients
Severe	67%	3-fold increase in patients
Extreme	75%	4-fold increase in patients

Table 17: Definition of Microsimulation Transition States

Transition State	Definition
Hospital	Initial state for all patients, may include Green patients who do not meet criteria for ICU resource allocation
ICU	Patients who are allocated ICU resources
Out	Patients who are removed from ICU
Expired	Absorbing state, patients who died in simulation

Transition probabilities represent the chance that a patient moves from one state to another and can vary by individual patient in microsimulation models. The transitions in this simulation are denoted by the arrows in Figure 8. Possible directions of transition are indicated by arrowheads. The transition probabilities are referred to as p_{AB}, where the subscripts A and B represent the initial state and final state, respectively. For example, p_{HI} represents the transition

probability for moving from Hospital to ICU. The eight transition probabilities are summarized in Table 18.

Table 18: Transition Probabilities and Definitions

Transition Probability	Conditional On		Definition
	Triage Category	Initial State	
p_{HI}	☑		Probability of being admitted to the ICU once hospitalized
p_{IH}	☑		Probability of transitioning out of the ICU back to the hospital ward
p_{HO}	☑		Probability of ICU bed being withheld once hospitalized
p_{OH}	☑		Probability of no longer requiring ICU after ICU bed withdrawn
p_{IO}	☑		Probability of ICU bed being withdrawn
p_{OI}	☑		Probability of being readmitted to the ICU after bed has been withdrawn
p_{IE}		☑	Probability of death while in the ICU
p_{OE}		☑	Probability of death after ICU bed withdrawn

As stated previously in this chapter, it is important to note that our microsimulation model examines the dynamics of resource allocation related to implementation of the SRAP. In that sense, the transition probabilities are not defined a priori but are determined by the allocation outcomes of each patient in the simulation category. In this analysis, the transition probabilities are calculated after each simulation to understand their variability as a function of resource constraint and allocation priority. This is possible because the SRAP determines the allocation decision of each patient according to their Triage Category, and these allocation decisions are captured per cycle as presence in the "ICU" or "Out" transition states.

The microsimulation models the application of the SRAP to a cohort of ICU patients using the variables shown in Figure 12.

Patient ID	Study Day	Death Day	Triage Code	Initial State	Final State

Figure 12: Simulation Data Structure

Study day is an integer value defined as the number of days between the study date and the beginning of the study, such that study day 0 corresponds to the first day of the study, May 26, 2021. The *death day* variable is a binary value that is 1 if the patient's *death date* (from the Patient Identifiers file) is equal to the study date, and 0 otherwise. This set of patients is then processed using the following steps:

1. Each patient starts the simulation in the Hospital state, represented by the *Initial State* assigned "Hospital."

2. During each cycle, corresponding to a calendar day, the patients are arranged in descending order of *Triage Code*. *Triage Code* is derived from the *Triage Category* as described in Table 19, reflecting the order of priority for ICU beds such that 1 reflects highest priority.

Table 19: Triage Categories and Corresponding Triage Codes

	Triage Category	Triage Code
Exemption Criteria	Violet	1
Acute Illness + Comorbidities	Red	2
	Orange	3
	Yellow	4
Catastrophic Conditions	Blue	5
Absence of ICU Indications	Green	6

3. Patients transition to the ICU state, represented by the *Final State* assigned "ICU" unless:

    a. Their position in the list is greater than the set ICU capacity, in which case the *Final State* is assigned "Out,"

    b. They have a *Triage Category* of Green, in which case the *Final State* is assigned "Hospital," or

42

c. They are known to have expired, indicated by *Initial State* assigned "Expired" or *Death Day* equal to 1, in which case the *Final State* is assigned "Expired."

4. Eight indicator variables – *HI*, *HO*, *IH*, *OH*, *IO*, *OI*, *IE*, *OE* – matching the 8 transition probabilities were defined to capture each patient's movement between states on a given day. Each variable was set to 1 if the patient started and ended in the corresponding states and 0 otherwise.

5. At the end of each day, the number of patients, in total and by Triage Category, in each state was calculated.

Model Assumptions

The assumptions included in the microsimulation model reflect the implemented resource allocation policy and are as follows:

1. *All-or-nothing*: Critical care resources are bundled and cannot be dissolved – that is, a patient who is not assigned to an ICU bed cannot receive component resources such as mechanical ventilation or continuous renal replacement therapy. In the context of our simulation, only patients in the "ICU" state receive critical care resources.

2. *Random allocation*: If critical care resources are not available for all patients within a given Triage Category, all patients (including those already receiving ICU resources) are randomly allocated the available resources – that is, patients of the same Triage Category have an equal probability of receiving critical care resources. In the simulation, patients are randomly ordered every study day, regardless of their simulation state (except Expired), to determine allocation of critical care resources.

3. *Non-allocation mortality*: ICU-eligible patients are only removed from an ICU bed under the policy if there exists another patient in an equal or higher Triage Category. Any patient who is removed from an ICU bed under these circumstances is assumed to continue to meet allocation criteria for critical care resources. If the patient is unable to

43

receive critical care resources within 1 day, probability of mortality (referred to as the non-allocation mortality) is 100 percent.

4. The "Expired" state is absorbing, meaning that patients do not transition out of the state.

Operationalization of non-allocation mortality was achieved by counting the number of cycles spent in the "Out" state. In the base case scenario, this meant that any patient for whom the final state was "Out" in both the current cycle and the previous cycle would transition to a final state of "Expired" in the current cycle. Cohort mortality was determined by counting the number of patients in the "Expired" state at the end of each simulation. The simulation runs are defined by three (3) variables:

- N, the number of ICU beds available;

- S, the number of simulations to run; and

- Dc, the number of cycles after which any patient who has not been allocated an ICU bed in the "Out" state expires ("non-allocation mortality clock").

The cycle unit in the simulation is one (1) day. After each cycle, a mortality indicator is recorded for each patient. At the end of each simulation, the cohort mortality is calculated. Each scenario was run one thousand (1000) times for an identical number of cycles representing the length of the initial data collection, sixty-eight (68) days.

Statistical Analysis

As discussed in the Key Variables subsection, e*xpired fraction* is used as the outcome variable in a linear regression as a summary measure of mortality in the simulation. Univariate logistic regression was performed for select Patient Characteristics variables and Policy Criteria variables to determine the unadjusted impact of each on mortality with *expired fraction* as the outcome of interest.

Expired fraction is converted to *expired counts* by multiplying by 1000, returning the number of simulations in which a patient expired. This is then used as the outcome variable in a negative binomial regression as the summary measure of mortality in the simulation.

The resulting mortality outcomes from the simulation scenarios (both *expired fraction* and *expired counts*) were non-normal in distribution. Most scenarios demonstrated a bimodal distribution, which made mean and median values imprecise summary statistics to describe the population. To determine the differences in outcomes across constraint levels, we defined mortality profiles for each scenario by dividing the population into three mortality groups:

- Patients who always died ("always"), for whom *expired fraction* equals 1;
- Patients who never died ("never"), for whom *expired fraction* equals 0; and
- Patients who sometimes died ("sometimes"), for whom *expired fraction* was any value greater than 0 or less than 1.

We performed Friedman rank sum testing to determine significant differences in the proportions across each constraint level.

In the multivariable analysis, we defined five models to examine the relationships between patient and/or policy factors and mortality. In the final, most comprehensive model, we performed two types of regression analyses: linear regression with *expired fraction* as the dependent variable, and negative binomial regression with *expired counts* as the dependent variable. In all other models, our analyses were limited to the linear regression approach.

In the first model, we examined the policy as written by testing the association between the SOFA Component and Comorbidity Component and mortality. In the second model, we deconstructed the Policy Criteria variables and examined the association of the uSOFA score and the individual prespecified comorbidities with mortality. In the third model, we incorporated the Patient Characteristics to determine how accounting for these variables impacted the association of Triage Category with mortality. We modified this approach in the fourth model by replacing Triage Category with the SOFA Component and Comorbidity Component variables.

Finally, in the fifth model, we again deconstructed the Policy Criteria variables and examined how the addition of the Patient Characteristics impacted the association of these variables with mortality. In addition to performing the different regressions described above for Model 3, we also performed the linear regression under the defined constraint levels to examine how these associations varied with resource constraint.

We performed a sensitivity analysis around the non-allocation mortality clock assumption by varying the *dc* simulation variable over the values 1 through 3, calculating the mortality profiles for each constraint level across these three values, and performing the Friedman rank sum test across the resulting table to look for statistically significant differences.

All analyses were conducted in R[35] and Microsoft Excel.[43]

Results

The Patient Characteristics and Policy Criteria variables among the study population are described in Table 20 and Table 21. The patients were majority male, not Hispanic or Latino, and English-speaking. Data was largely unknown for sexual orientation and gender identity.

The mortality profile for each constraint level is shown in Table 22. The proportion of patients with 100 percent risk of mortality under the allocation policy rose by 56 percent under severe constraint and by 62.5 percent under extreme constraint. The Friedman rank sum test of proportions suggested a significant difference in the mortality profiles of the cohort across constraint levels. Given this result, we performed a Wilcoxon signed rank test for each of the constraint pairs: base-moderate, base-severe, base-extreme, moderate-severe, moderate-extreme, and severe-extreme. The p-values for all these tests were less than 0.001, suggesting a significant difference in the mortality outcomes between any of the defined constraint levels.

Table 20: Demographic composition of study population

Patient Characteristics	N (%)[1]
Total Number of Unique Patients	963
Age (Years), mean [SD]	59.5 [17.0]
Sex	
Male	557 (57.8%)

46

Patient Characteristics	N (%)[1]
Female	406 (42.2%)
Race	
White or Caucasian	405 (42.1%)
Black or African American	103 (10.7%)
American Indian or Alaska Native	2 (0.2%)
Asian	81 (8.4%)
Middle Eastern or North African	17 (1.8%)
Native Hawaiian or Other Pacific Islander	5 (0.5%)
Multiple Races	28 (2.9%)
Do Not Identify	17 (1.8%)
Other	245 (25.4%)
Unknown	60 (6.2%)
Ethnicity	
Hispanic or Latino	213 (22.1%)
Not Hispanic or Latino	663 (68.8%)
Other	51 (5.3%)
Unknown	36 (3.7%)
Marital Status	
Partnered	468 (48.6%)
Not Partnered	488 (50.7%)
Unknown	7 (0.7%)
Sexual Orientation	
Straight	420 (43.6%)
Lesbian or Gay	22 (2.2%)
Bisexual	4 (0.4%)
Other	3 (0.3%)
Unknown	514 (53.3%)
Gender Identity	
Male	256 (26.6%)
Female	221 (22.9%)
Transgender Male	2 (0.2%)
Unknown	484 (50.2%)
Language	
English	804 (83.5%)
Non-English	157 (16.3%)
Unknown	2 (0.2%)

[1]Unless otherwise specified

Table 21: Description of triage encounters by policy criteria

Policy Criteria	N (%)[1]
Total Number of Triage Encounters	3626
uSOFA Score, median [IQR]	7 [5-11]
SOFA Component	
1	672 (18.5%)
2	683 (18.8%)
3	339 (9.3%)
4	324 (8.9%)
N/A[2]	1608 (44.3%)
Comorbidity Component	
0	705 (19.4%)
2	313 (8.6%)
4	965 (26.6%)
Unknown/Unavailable	35 (1.0%)
N/A[2]	1608 (44.3%)
Prespecified Comorbidities	
Comorbidity M1	81 (2.2%)
Comorbidity M2	182 (5.0%)

Policy Criteria	N (%)[1]
Comorbidity M3	20 (0.6%)
Comorbidity M4	94 (2.6%)
Comorbidity M5	27 (0.7%)
Comorbidity M6	268 (7.4%)
Comorbidity M7	52 (1.4%)
Comorbidity S1	22 (0.6%)
Comorbidity S2	234 (6.5%)
Comorbidity S3	75 (2.1%)
Comorbidity S4	230 (6.3%)
Comorbidity S5	367 (10.1%)
Comorbidity S6	102 (2.8%)
Comorbidity S7	33 (0.9%)
Triage Category	
Violet	620 (17.1%)
Red	769 (21.2%)
Orange	478 (13.2%)
Yellow	723 (19.9%)
Blue	62 (1.7%)
Green	974 (26.9%)

[1]Unless otherwise specified
[2]Represents Violet, Blue, and Green patients for whom data collection did not occur

Table 22: Mortality profile by constraint level

Constraint Level	Proportion of Patients		
	Always	**Sometimes**	**Never**
Base	0.032	0	0.968
Moderate	0.032	0.194	0.774
Severe	0.05	0.359	0.59
Extreme	0.052	0.434	0.513

Friedman rank sum: $p = 0.039$

The results of linear regression models of expired fraction are shown in Table 23 and

Table 24. The variables *sexual orientation* and *gender identity* were omitted given the large

proportion of unknown values in the patient population and because we lacked a specific

hypothesis of their relevance to the outcome of interest. Patient Characteristics variables were

largely unassociated with mortality in these unadjusted analyses. Native Hawaiian or Other

Pacific Islander race was associated with relatively large increases in *expired fraction* across

constraint levels, including the base case, although the small sample size should be noted.

Table 23: Univariate Logistic Regression of Selected Patient Characteristics Variables on 100 x Expired Fraction

		Coefficients by Constraint Level			
	N	**Base**	**Moderate**	**Severe**	**Extreme**
Patient Characteristics					
Age	954	0.06	0.004	-0.01	-0.07
Sex					
Male	557	Reference			
Female	406	1.67	4.788	0.63	0.66
Race					

	N	Coefficients by Constraint Level			
		Base	**Moderate**	**Severe**	**Extreme**
White or Caucasian	405	Reference			
Black or African American	103	-0.05	0.73	2.70	3.80
Asian	81	4.44*	1.50	3.58	5.32
Native Hawaiian or Other Pacific Islander	5	17.04*	29.13*	28.90*	30.66*
Middle Eastern or North African	17	-2.96	-7.05	-0.99	1.21
American Indian or Alaska Native	2	-2.96	-10.36	-10.02	-20.10
Multiple Races	28	-2.96	-8.77	-10.22	-8.70
Do Not Identify	17	-2.96	0.77	-0.76	-3.85
Other	245	0.71	1.51	3.13	5.16
Unknown	60	-2.96	-5.98	-6.40	-5.88
Ethnicity					
Not Hispanic or Latino	663	Reference			
Hispanic or Latino	213	0.59	2.47	5.45*	8.39**
Other	51	0.75	5.75	6.67	5.40
Unknown	36	-3.17	-9.22*	-12.49*	-13.32*
Language					
English	804	Reference			
Non-English	157	1.47	6.57**	11.18**	10.86***
Unknown	2	-2.98	-9.44	-16.52	-15.28

* p < 0.05; ** p < 0.01; *** p < 0.001

Table 24: Univariate Logistic Regression of Policy Criteria Variables on 100 x Expired Fraction

	N	Coefficients by Constraint Level			
		Base	**Moderate**	**Severe**	**Extreme**
Policy Criteria					
SOFA Component	455	4.76***	11.73***	12.04***	9.09***
uSOFA Score	455	1.24***	2.77***	2.81***	2.11***
Comorbidity Component					
0	204	Reference			
2	83	3.57	14.68***	27.42***	21.98***
4	147	6.39***	38.69***	37.19***	22.14***
Unknown/Unavailable	21	-2.54	-2.78	-2.10	-3.91
Prespecified Comorbidities					
Comorbidity M1	22	-3.29	-0.33	3.29	5.69
Comorbidity M2	38	4.87	10.48*	37.25**	39.93***
Comorbidity M3	9	-3.25	8.14	24.85*	29.24*
Comorbidity M4	9	-3.25	21.11*	38.98***	53.26***
Comorbidity M5	3	-3.23	-4.67	11.26	12.99
Comorbidity M6	43	13.67***	37.21***	41.75***	38.95***
Comorbidity M7	14	3.98	7.70	19.98*	21.14*
Comorbidity S1	6	13.53	65.82***	44.7***	38.92**
Comorbidity S2	25	0.80	30.73***	43.63***	43.70***
Comorbidity S3	6	-3.24	44.72***	30.66*	24.15
Comorbidity S4	37	13.51***	45.64***	45.39***	40.53***
Comorbidity S5	58	7.58**	41.41***	37.47***	29.36***
Comorbidity S6	31	16.67***	26.18***	34.35***	28.57***
Comorbidity S7	8	-3.25	5.97	17.95	14.64
Triage Category					
Violet	221	Reference			
Red	228	0.84	3.15	10.93***	24.23***
Orange	98	0.68	14.58***	43.49***	48.77***
Yellow	112	11.14***	49.19***	51.27***	47.94***
Blue	20	18.64***	32.29***	30.58***	37.77***
Green	284	-0.30	0.76	1.33	0.17

* p < 0.05; ** p < 0.01; *** p < 0.001

Transition States

To understand the allocation of critical care resources, redistribution of those resources, mortality outcomes as a function of resource constraint, we generated stacked column charts for the ICU, Out, and Expired states under each constraint level. Each chart is constructed such that higher priority patients appear at the bottom of the stack.

The average daily patient census in the ICU is shown in Figure 13. These charts show the overall change in the breakdown of Triage Categories over the study period as the degree of constraint increases. In general, as the constraint level increases, lower priority patients are less represented in the ICU over the course of the study period.

The average daily number of patients in the Out state is shown in Figure 14. In the base case, patients are never removed from the ICU. As constraint level increases, the number of days during the study in which patients are removed increases, although even under the extreme constraint level, there remain days over the course of the study in which no patients are removed. The patients removed are of lower Triage Category levels, and under no constraint level are Violet patients removed from the ICU.

The average daily number of patients in the Expired state is shown in Figure 15. Most notable is that in the base case, patients do not expire every day, and that this changes immediately upon applying a constraint such that patient expire daily. Under moderate constraint, most deaths occur in the lowest priority patients. Under severe and extreme constraints, there appears to be an emergence of deaths among Green patients who were deemed to be stable, not requiring critical care. This is an artifact of the simulation – as patients are removed from the ICU under varying constraint levels, their historical Triage Category values were not changed. Thus, some patients transitioned from ICU to Out to Expired, and while in the Expired state, took on a Triage Category value of Green. As their updated Triage Category occurred while in the Expired state, they appear among the expired patients for that study day.
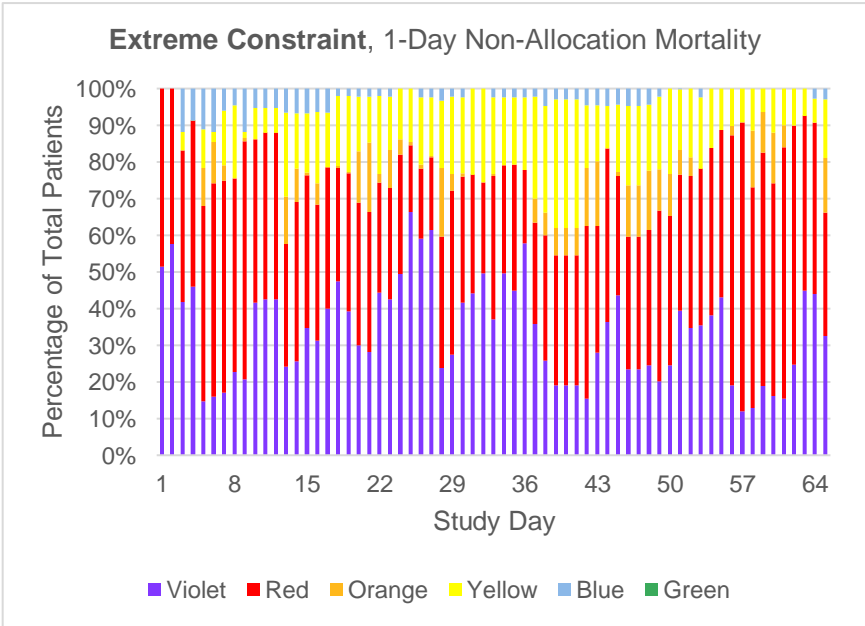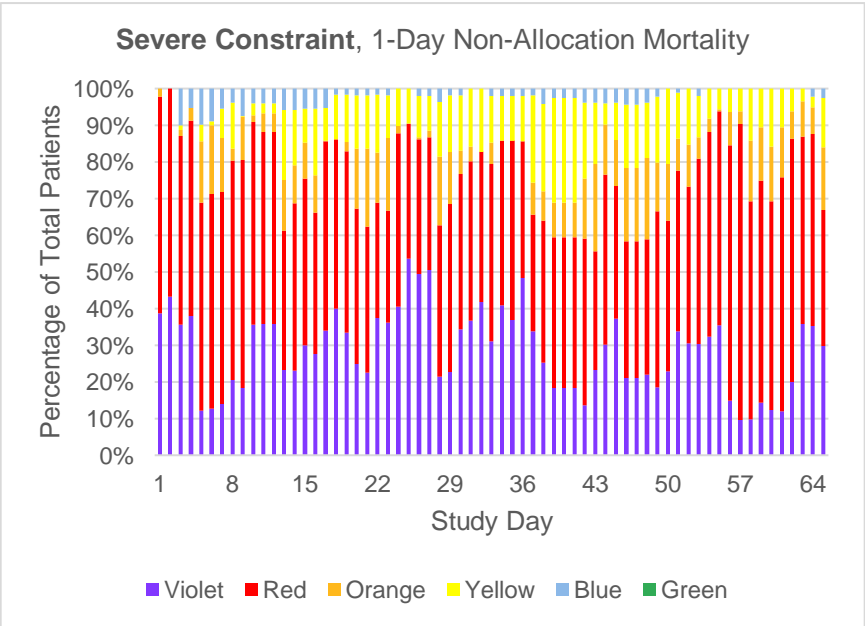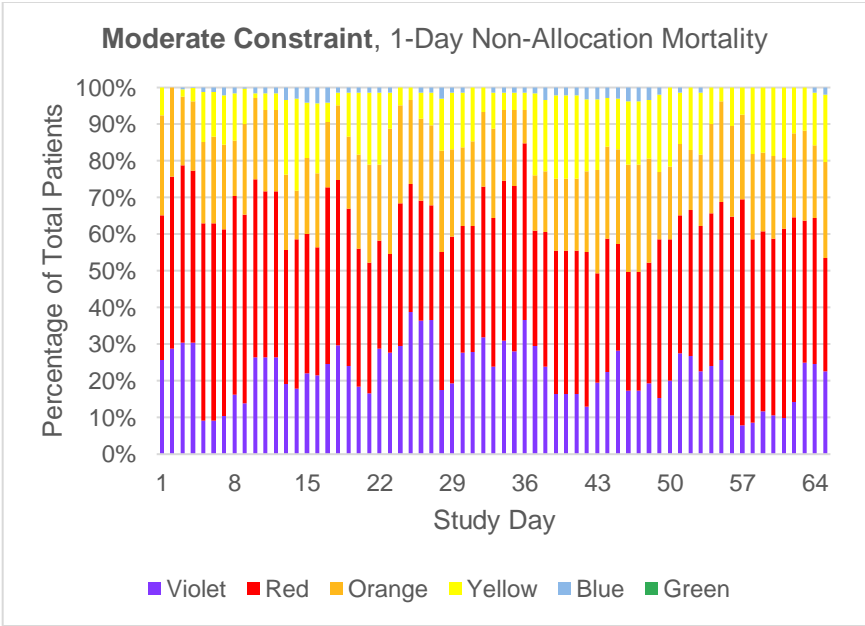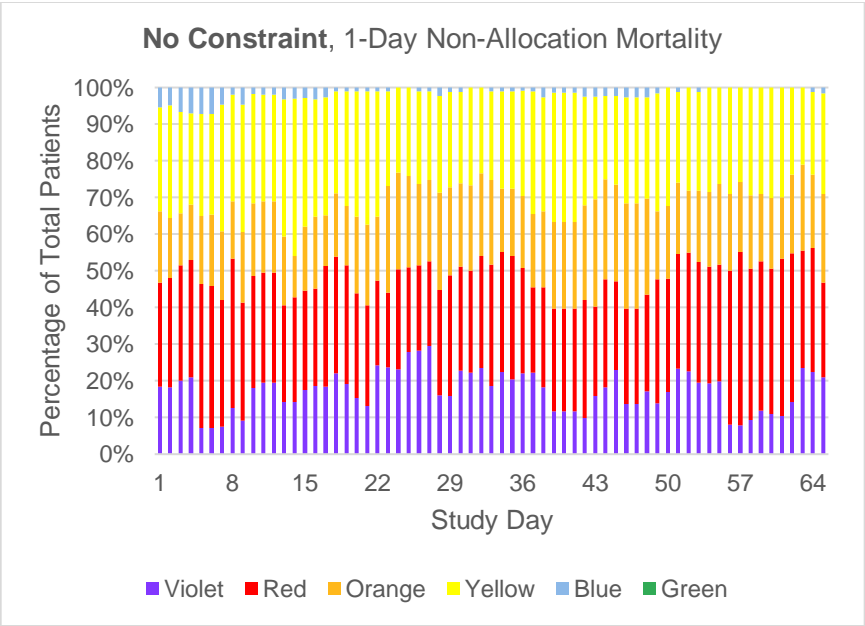
Figure 13: Average Daily Patients in ICU by Constraint Level
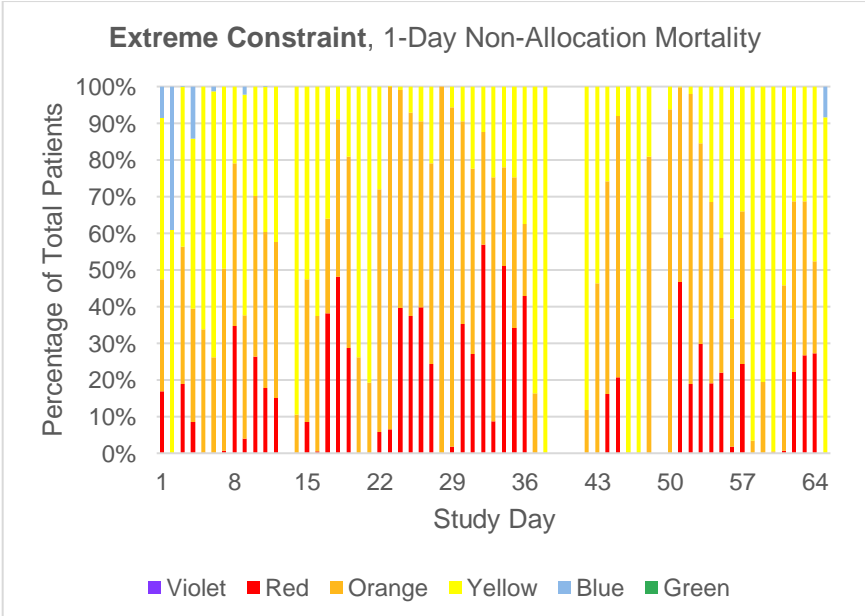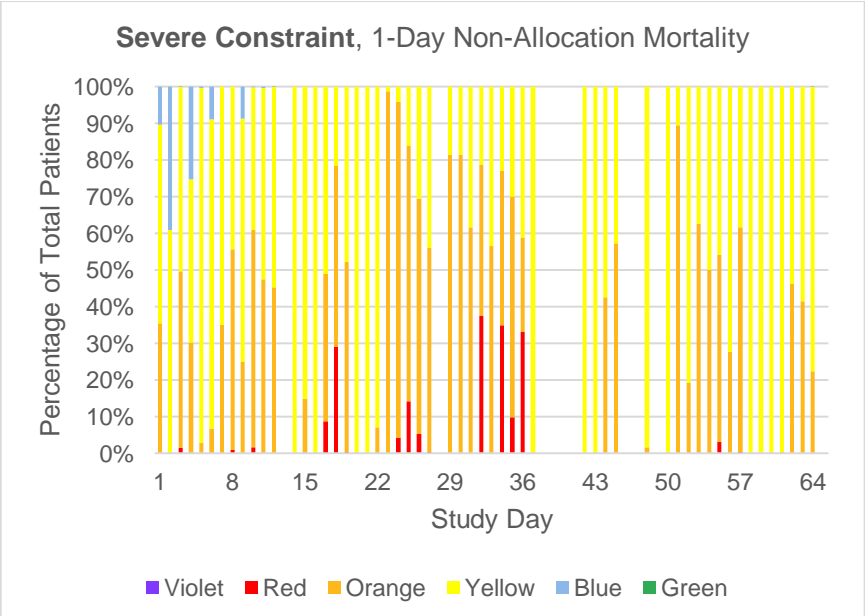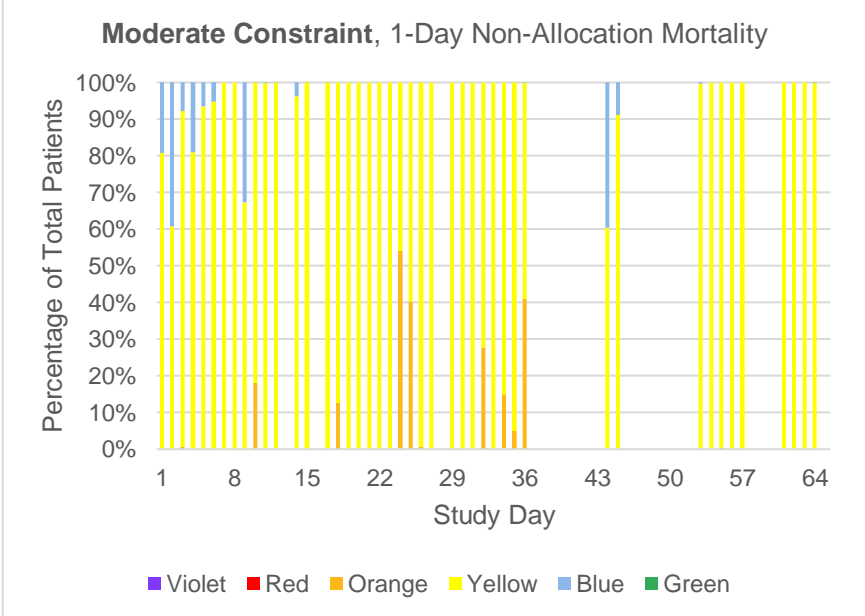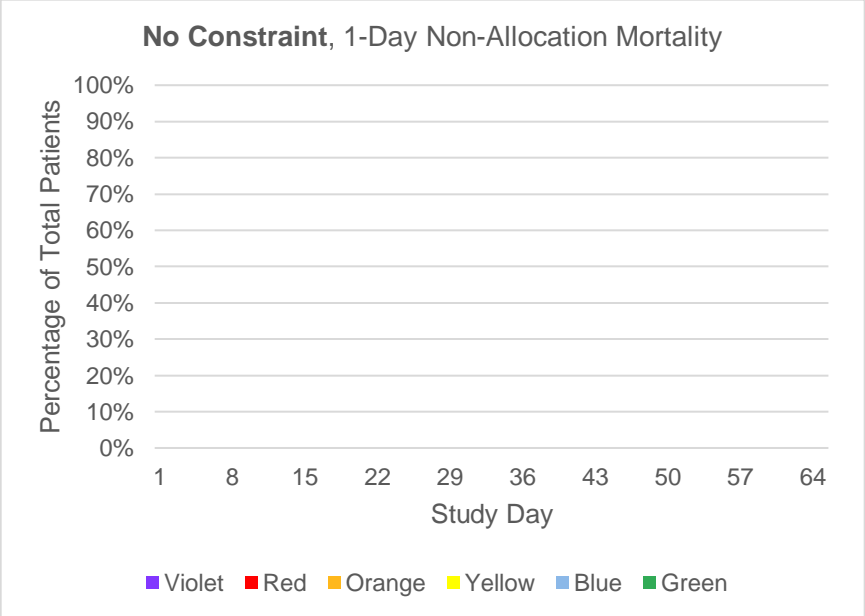
Figure 14: Average Daily Patients Removed from ICU by Constraint Level

52
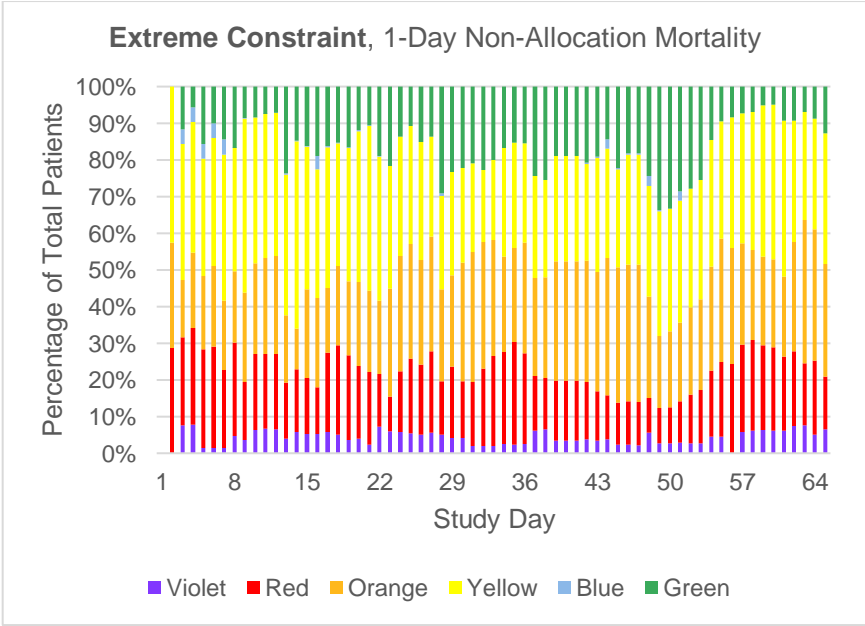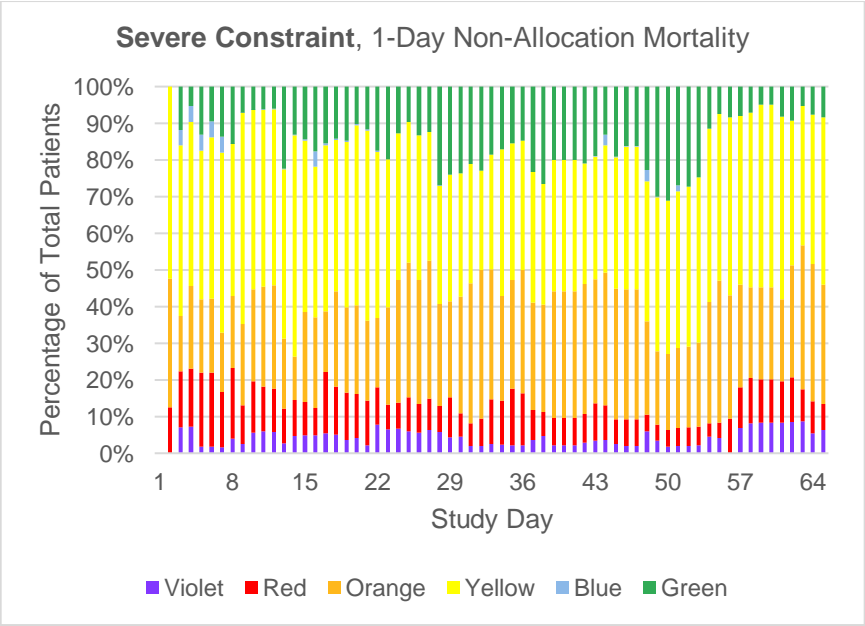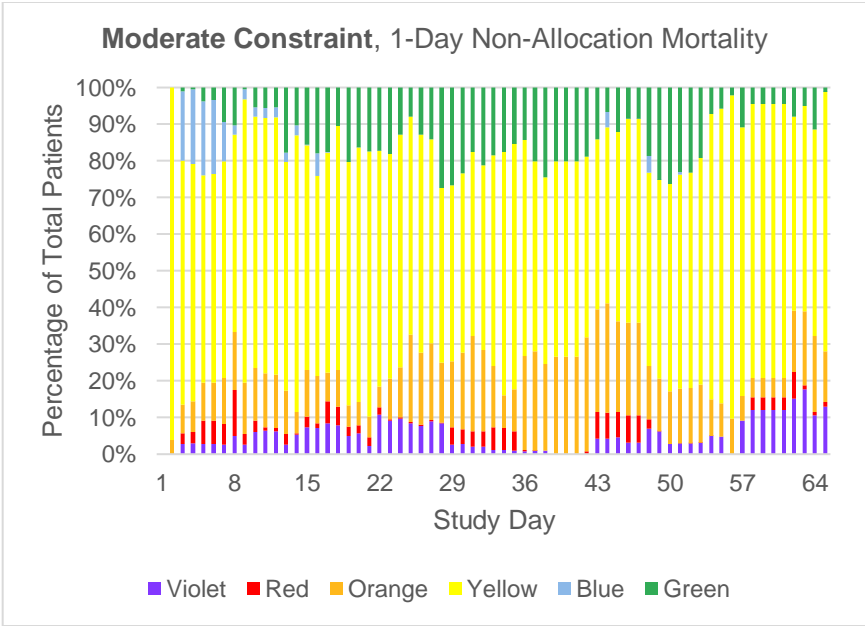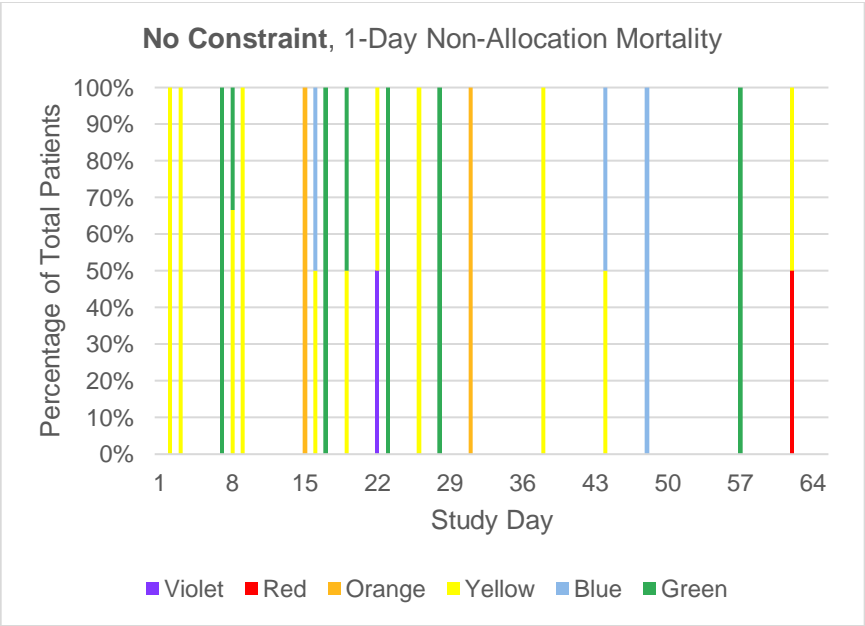
Figure 15: Average Daily Mortality by Constraint Level

Transition Probabilities

To understand how resource allocation and re-allocation differed by constraint level, we constructed bar plots for each Triage Category under each constraint level for specific transition probabilities. In each plot, there are three lines for each Triage Category, each line representing conditions under each non-allocation mortality clock scenario. The diamond marker denotes the median value of the transition probability over the study period with the pipe symbols and horizontal bars connecting them represent the interquartile range (IQR). The individual dots represent the average daily transition probability for the specified group for each day in the study over the 1000 simulations. The number of dots per Triage Category group varies, as some groups did not undergo the specified transition every day. The groups are arranged from the origin in order of descending priority.

The transition probability for going from "Hospital" to "ICU" (p_{HI}), or the probability of receiving an ICU bed once hospitalized, is shown in Figure 16. This probability was 0 for Green patients (those without ICU indications) across the constraint levels, as by definition these patients were not allocated ICU beds due to lack of indication. Under moderate constraint, there were some days during which the lowest priority Blue (catastrophic conditions) and Yellow (highest Triage Allocation Scores) patients were less likely to receive ICU beds, but the median value was still 1. Under severe and extreme constraint, these distributions shift farther to the left for all patients except Violet, indicating lower likelihood of allocation of critical care resources as constraint increases.

Figure 17 shows the transition probability for going from "Hospital" to "Out" (p_{HO}), or the probability of having an ICU bed withheld once hospitalized. Again, this probability was 0 for Green patients across constraints, reflecting that these patients did not have indications for ICU and remained in the "Hospital" state. As constraint level increases, the distribution of this

54

probability shifts to the right for patients of lower priority, reflecting a general increase in the likelihood that an ICU bed is withheld.

Figure 18 shows the transition probability for going from "ICU" to "Out" (p_{IO}), or the probability of having an ICU bed withdrawn. These plots show that the likelihood of being removed of the ICU increases first for lower priority patients (Yellow under moderate constraint), but eventually increases for all but the highest priority patients (Violet) as constraint increases to extreme levels.

Figure 19 shows the transition probability for going from "Out" to "ICU" (p_{OI}), or the probability of being readmitted to the ICU after having a bed withdrawn. In the base case, beds are available for all patients, so patients never end up in the "Out" state and thus this probability cannot be calculated. Under even moderate constraint, patients may have beds withheld, but the median likelihood of being admitted is 100 percent for the highest priority patients (Violet, Red, and Orange) and high but less than 100 percent for the lower priority Yellow patients. These distributions shift to the left with increasing constraint for all groups except Violet, reflecting lower likelihood of readmission to the ICU as resources become less available.

The base case transition probabilities serve to validate that the simulation operated as intended. As can be seen in the figures, all patients receive an ICU bed (p_{HI} equals 1), no patients have beds withheld, and no patients have beds withdrawn. Probability of being readmitted to the ICU after having a bed withdrawn (p_{OI}) cannot be calculated in the base case as patients never transition to the "Out" state.

In general, the Blue patients appear to be less subject to fluctuations in transition probability as a function of constraint level, but this is likely due to the relatively small number of encounters (1.7%) with Blue priority levels, such that Blue patients were not represented on most days during the study period.
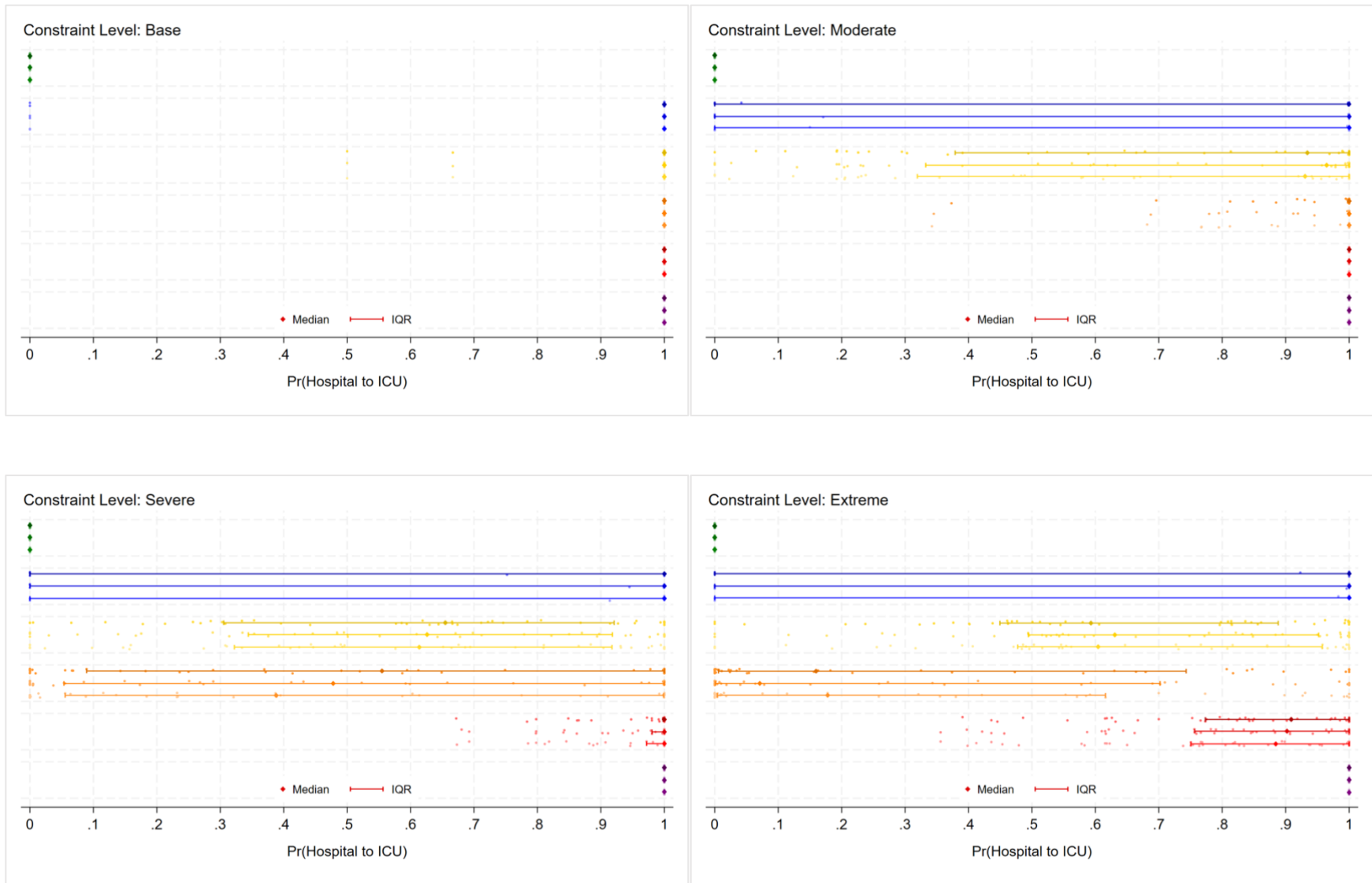
Figure 16: Probability of being admitted to the ICU once hospitalized by constraint level
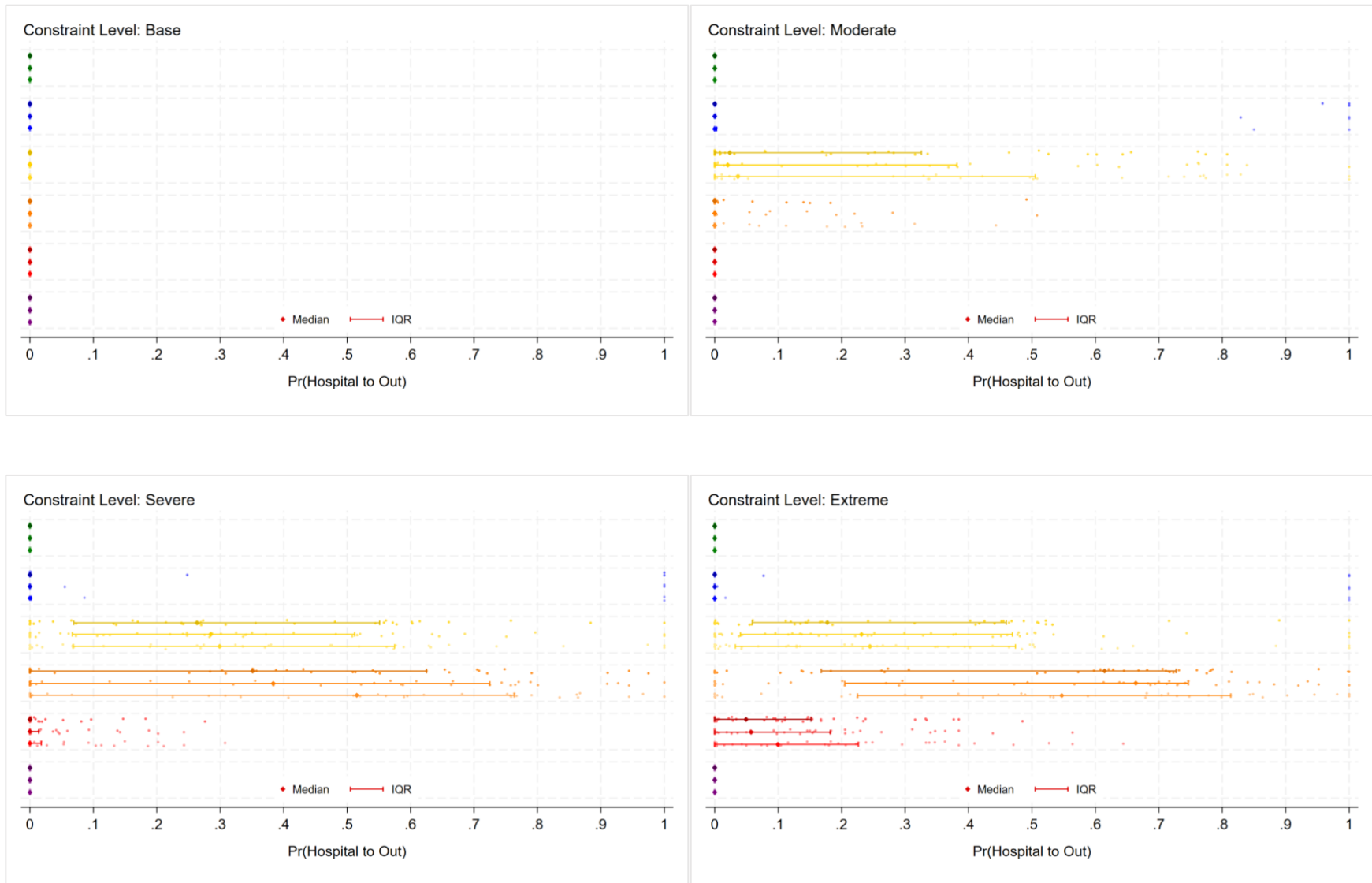
Figure 17: Probability of ICU bed being withheld once hospitalized by constraint level
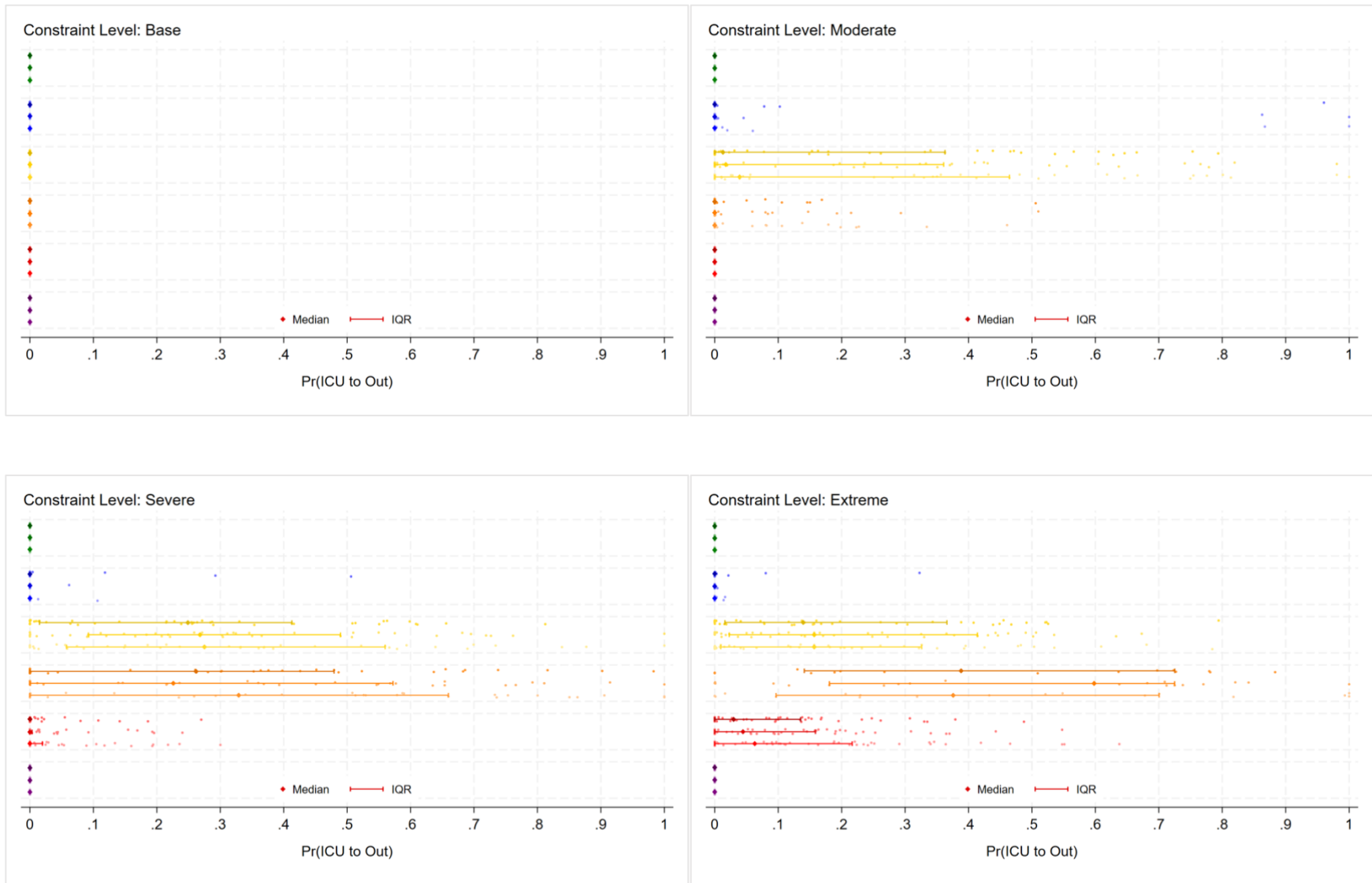
Figure 18: Probability of ICU bed being withdrawn by constraint level
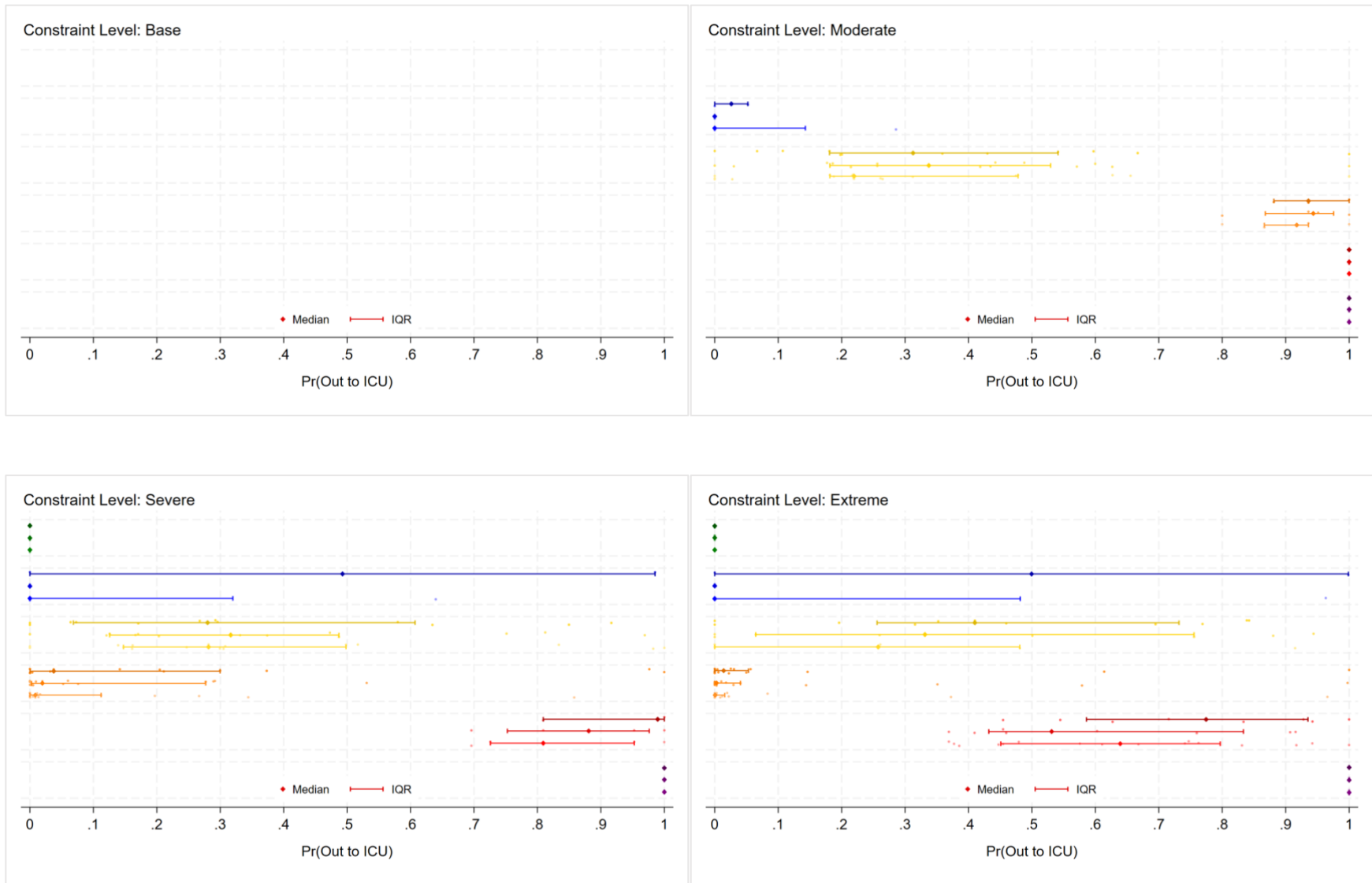
Figure 19: Probability of being readmitted to the ICU after bed has been withdrawn by constraint level

Multivariable Analyses

The coefficients for the multivariable linear regressions in the base case scenario are shown in Table 25. In Models 1 and 2, the Policy Criteria representing the objective measure of acute illness was significantly associated with an increased risk of mortality, when not accounting for Patient Characteristics. A 1-point increase in the SOFA Component was associated with an increase in *expired fraction* of 0.044, and a 1-point increase in the uSOFA score was associated with an increase in *expired fraction* of 0.012. The Policy Criterion representing co-occurring illnesses was not significantly associated with mortality in Model 1, but when disaggregated into its component parts in Model 2, specific comorbidities were found to have a significant association with risk of mortality, again not accounting for Patient Characteristics.

Model 3 represents the operationalization of the Policy as written and effectively builds on the univariate analysis of Triage Category shown in Table 24 by incorporating Patient Characteristics. All else equal among the selected Patient Characteristics, Yellow and Blue Triage Categories remained significantly associated with increased risk of mortality. Notably, Asian race was significantly associated with increased risk of mortality, holding constant the allocation priority level. The impact of age was small but also statistically significant, predicting a 0.0007-point increase in *expired fraction*.

Models 4 and 5 represent the incorporation of Patient Characteristics into Models 1 and 2. Again, as in models 1 and 2, the SOFA Component in model 4 and uSOFA score in model 5 were significantly associated with increase in expired fraction, with each variable predicting an increase of 0.046 and 0.013, respectively. Age remained statistically significant in these models, associated with a 0.0013-increase in *expired fraction*.

Table 25: Coefficients of various linear regression models with expired fraction as outcome

Variable	Coefficients for selected variables against 100 * *expired fraction*				
	Model 1	Model 2	Model 3	Model 4	Model 5
Patient Characteristics					
Age	-		0.07*	0.13*	0.13*
Sex					

Variable	Coefficients for selected variables against 100 * *expired fraction*				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Male	Reference				
Female	-		1.36	3.80	3.74
Race					
White or Caucasian	Reference				
Black or African American	-		0.49	1.62	-0.08
Asian	-		5.10*	10.99**	9.74*
Native Hawaiian or Other Pacific Islander	-		15.14	29.56*	24.23
Middle Eastern or North African	-		-1.53	-2.02	-2.66
American Indian or Alaska Native	-		0.09	NC	NC
Multiple Races	-		-1.08	-3.14	-1.40
Do Not Identify	-		-3.99	-7.16	-5.45
Other	-		0.15	1.77	2.31
Unknown	-		-2.36	-3.36	-2.06
Ethnicity					
Not Hispanic or Latino	Reference				
Hispanic or Latino	-		2.43	3.19	2.44
Other	-		1.10	-2.62	-4.58
Unknown	-		0.44	2.29	-0.86
Language					
English	Reference				
Non-English	-		-0.78	-1.61	-2.23
Unknown	-		3.65	9.97	11.74
Policy Criteria					
SOFA Component	4.38***		-	4.58***	-
uSOFA score	-	1.21***	-	-	1.28***
Comorbidity Component					
0	Reference				
2	3.01		-	3.09	-
4	3.69		-	3.38	-
Unknown/Unavailable	-3.22		-	-3.53	-
Prespecified Comorbidities					
Comorbidity M1	-	-5.31	-	-	-4.41
Comorbidity M2	-	5.85	-	-	5.76
Comorbidity M3	-	-5.92	-	-	-3.32
Comorbidity M4	-	-1.25	-	-	-0.27
Comorbidity M5	-	-2.91	-	-	-3.71
Comorbidity M6	-	7.98*	-	-	8.47*
Comorbidity M7	-	3.05	-	-	2.88
Comorbidity S1	-	4.02	-	-	5.54
Comorbidity S2	-	2.67	-	-	3.29
Comorbidity S3	-	-7.49	-	-	-10.57
Comorbidity S4	-	10.0**	-	-	8.88*
Comorbidity S5	-	-1.89	-	-	-2.19
Comorbidity S6	-	15.3***	-	-	13.82***
Comorbidity S7	-	-6.29	-	-	-10.32
Triage Category	-				
Violet	Reference				
Red	-	-	0.70	-	-
Orange	-	-	0.41	-	-
Yellow	-	-	10.7***	-	-
Blue	-	-	18.3***	-	-
Green	-	-	-0.55	-	-
Model Diagnostics					
N	455	455	954	449	449
Adjusted R^2	0.05	0.11	0.05	0.07	0.12
AIC	4084.34	4067.01	8162.35	4042.03	4026.86

	Coefficients for selected variables against 100 * *expired fraction*				
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

* p < 0.05; ** p < 0.01; *** p < 0.001
NC: not calculated

Table 26 shows the regression results for Model 3 across various constraint levels. This model
was chosen specifically to examine how the policy's operationalization of allocation priority
varied with constraint levels when holding patient factors constant. With regards to the Patient
Characteristics variables, age became statistically significant under all constraint levels when
accounting for triage allocation priority. Female sex was significantly associated with a 0.033-
increase in *expired fraction* under moderate constraint, but was not significant under severe and
extreme constraints, holding Triage Category constant. Asian race was no longer a significant
predictor of risk of mortality when resources were constrained compared to White or Caucasian
race. Non-English preferred language was significantly associated with increased risk of
mortality when compared to English speakers, holding allocation priority and all other selected
patient factors constant, predicting an *expired fraction* increase of 0.069 under severe constraint
and 0.058 under extreme constraint.

Table 26: Coefficients for model 3 linear regression by constraint level

Model 3: Patient Characteristics and Triage Category on 100 * *expired fraction*				
	Constraint Level			
Variable	Base	Moderate	Severe	Extreme
Patient Characteristics				
Age	0.07*	0.00	-0.02	-0.06
Sex				
Male	Reference			
Female	1.36	3.34*	0.09	0.81
Race				
White or Caucasian	Reference			
Black or African American	0.49	-1.27	-0.91	-0.47
Asian	5.10*	1.44	3.43	5.00
Native Hawaiian or Other Pacific Islander	15.14	14.75	12.94	17.54
Middle Eastern or North African	-1.53	-3.57	3.81	6.22
American Indian or Alaska Native	0.09	-0.53	10.17	-1.08
Multiple Races	-1.08	-4.87	-6.21	-5.35
Do Not Identify	-3.99	-1.47	-3.44	-6.43
Other	0.15	-1.56	-1.57	-0.63
Unknown	-2.36	-2.59	-3.95	0.21
Ethnicity				
Not Hispanic or Latino	Reference			
Hispanic or Latino	2.43	1.95	2.88	4.85

Model 3: Patient Characteristics and Triage Category on 100 * *expired fraction*				
	Constraint Level			
Variable	**Base**	**Moderate**	**Severe**	**Extreme**
Other	1.10	-0.08	-0.16	0.94
Unknown	0.44	-2.53	-4.72	-4.11
Language				
English	Reference			
Non-English	-0.78	3.48	6.88*	5.81*
Unknown	3.65	3.09	-1.19	-1.73
Policy Criteria				
Triage Category				
Violet	Reference			
Red	0.70	2.76	10.28***	23.07***
Orange	0.41	14.19***	42.99***	48.06***
Yellow	10.7***	47.50***	49.74***	45.99***
Blue	18.3***	30.95***	28.28***	35.21***
Green	-0.55	0.26	1.12	-0.23
Model Diagnostics				
N	954	954	954	954
Adjusted R^2	0.05	0.35	0.33	0.33
AIC	8162.35	8576.67	9007.32	9110.03
p-value	< 0.001	< 0.001	< 0.001	< 0.001

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
NC: not calculated

To test the robustness of the assumptions relied upon in using a linear model, we evaluated model 3 as a count model. The results of the negative binomial regression are shown in Table 27. Unlike in the linear model, age was significantly associated with risk of mortality across constraint levels (except under moderate constraint), and female gender was consistently associated with increased risk of mortality. In general, race was not consistently associated with increased risk of mortality, except under severe constraint when American Indian or Alaska Native patients were at lower risk of mortality, Asian patients at no increased risk, and all other groups at slightly higher risk of mortality, compared to White patients. This pattern was unchanged under extreme constraint, except that Asian patients were now at increased risk, compared to White patients. Results for ethnicity were inconsistent across constraint levels, with all groups experiencing higher or lower risk of mortality compared to non-Hispanic or Latino patients depending on level of constraint. Non-English primary language was generally associated with higher risk of mortality, except in the base case. Finally, the Triage Category determination was almost always a significant predictor of mortality. Comparing all patients to the highest priority ICU-eligible patients (Violet), lower priority was typically

associated with higher risk of mortality. Yellow patients had a higher risk of mortality than the

lowest priority Blue patients across all constraint levels.

Table 27: Negative binomial regression coefficients (as incidence rate ratios) for model 3 by constraint level

Model 3: Patient Characteristics and Triage Category on *expired counts*				
	Constraint Level			
Variable	Base	Moderate	Severe	Extreme
Patient Characteristics				
Age	1.03***	0.99	1.00***	0.99***
Sex				
Male	Reference			
Female	1.91***	1.71***	1.02***	1.02***
Race				
White or Caucasian	Reference			
Black or African American	0.79***	0.83	1.02***	1.04***
Asian	4.53***	1.38	1.00	1.06***
Native Hawaiian or Other Pacific Islander	2.68***	1.97	1.33***	1.33***
Middle Eastern or North African	0	1.24	1.19***	1.18***
American Indian or Alaska Native	0	0.022	0.32***	0.07***
Multiple Races	0	0.18***	0.44***	0.61***
Do Not Identify	0	2.14*	1.65***	1.23***
Other	1.69***	0.99	1.04***	1.03***
Unknown	0	1.27	1.02***	0.91***
Ethnicity				
Not Hispanic or Latino	Reference			
Hispanic or Latino	2.95***	0.96	0.97***	1.07***
Other	0.89***	1.20	0.91***	0.89***
Unknown	0	0.067***	0.26***	0.42***
Language				
English	Reference			
Non-English	0.58***	1.49*	1.25***	1.16***
Unknown	5.00e14	0	0	0.44***
Policy Criteria				
Triage Category				
Violet	Reference			
Red	1.14***	0.85	1.62***	2.26***
Orange	1.33***	4.22***	4.51***	3.72***
Yellow	8.91***	8.53***	4.68***	3.47***
Blue	8.83***	5.82***	1.91***	1.71***
Green	0.98	1.35	1.31***	1.26***
Model Diagnostics				
N	923	923	923	923
Dispersion parameter	323449.3	0.1004	738424.7	1949407
Deviance (-2 x log-likelihood)	NC	-29903.7	NC	NC
AIC	711893	29950	1241942	1180913

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
NC: not calculated

Sensitivity Analyses

Bar charts showing the changes in mortality profile by non-allocation mortality clock are shown

in Figure 20. The Friedman rank sum test of proportions under each constraint level was

statistically significant, all with a p value of 0.0497, suggesting that the mortality profiles were

significantly different between clock values.

Given this result, we performed pairwise Wilcoxon signed-rank tests between the

expired fraction results comparing the non-allocation mortality clock assumption of 1 day to

assumptions of 2 days and 3 days under each level of constraint. This could not be performed

under the base constraint scenario, as the *expired fraction* outcome was identical across non-

allocation mortality clock values since beds always were available for every patient in the

simulation. The results for the comparisons within the moderate, severe, and extreme constraint

levels are shown in Table 28.

Table 28: Summary of distribution of expired fraction with varying non-allocation mortality clock

	Constraint Level								
	Moderate			Severe			Extreme		
Non-Allocation Mortality (days)	Mean	Median	IQR	Mean	Median	IQR	Mean	Median	IQR
1	0.105	0	(0, 0)	0.183	0	(0, 0.195)	0.235	0	(0, 0.414)
2	0.102	0	(0, 0)	0.181	0	(0, 0.208)	0.231	0	(0, 0.416)
3	0.093	0***	(0, 0)	0.170	0	(0, 0.198)	0.218	0***	(0, 0.382)

Results of Wilcoxon rank sum testing of difference in *expired fraction* distribution (compared to 1 day):
*p < 0.05; **p < 0.01; ***p < 0.001

These results suggest that, as non-allocation mortality clock increases, the proportion of

patients that sometimes expire in the simulation decreases, and the proportion of patients who

never expire increases. The statistical testing demonstrates no significant difference when the

non-allocation mortality clock increases from 1 to 2 but demonstrates a significant difference

when increasing from 1 to 3 (except for under the severe constraint).
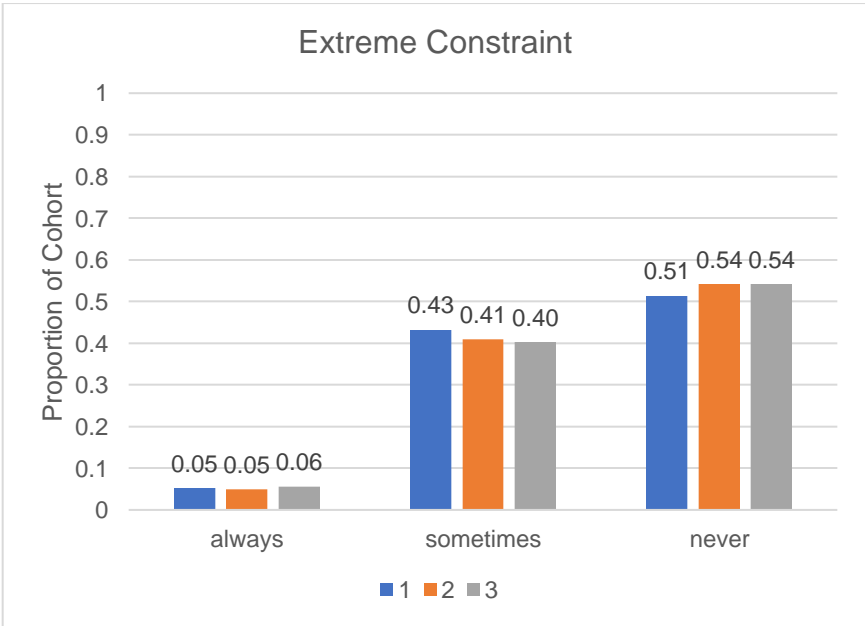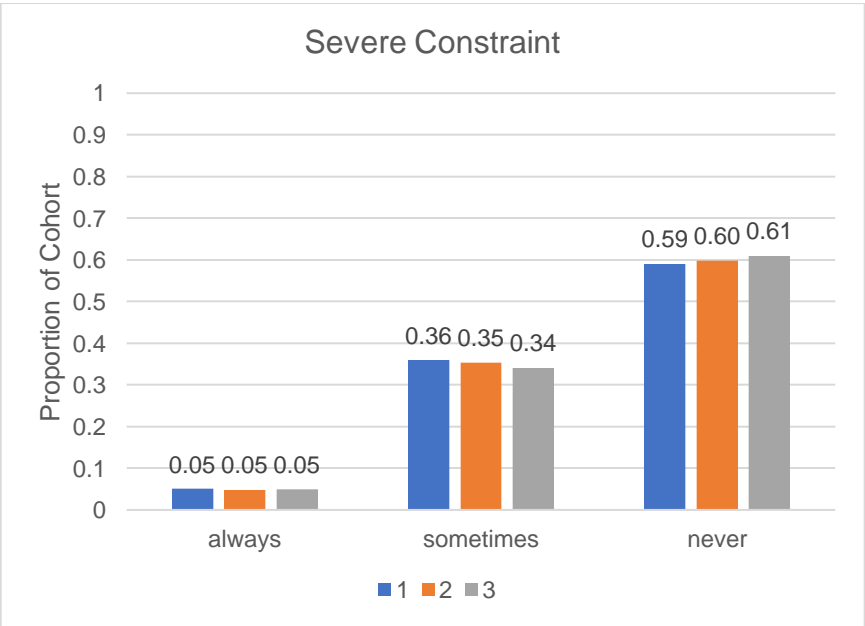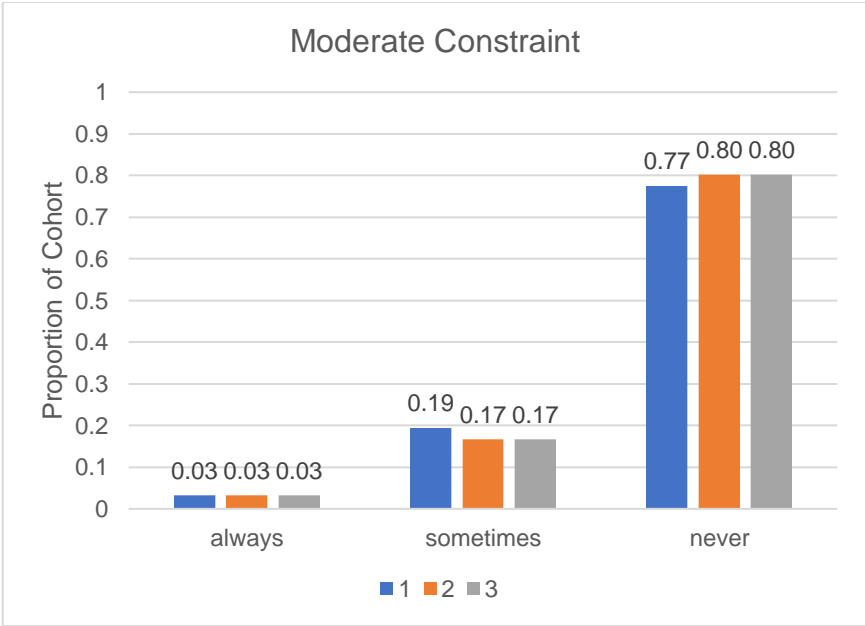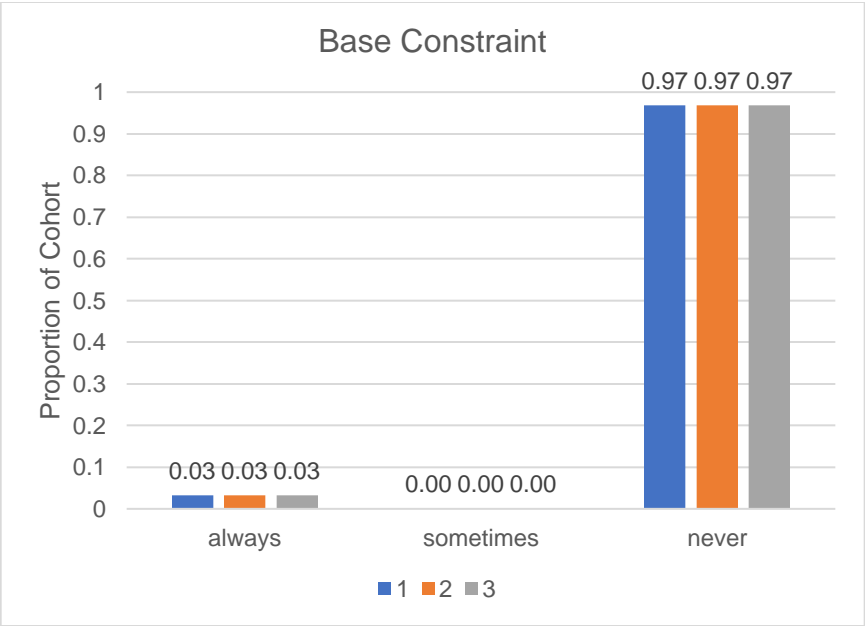
Figure 20: Mortality profile under varying non-allocation mortality assumptions by constraint level

Discussion

There are significant differences in the mortality profiles of the cohort across constraint levels. Our simulation results suggest that the SRAP does not lead to statistically similar risks of mortality for our cohort across different constraint levels as we hypothesized that it would. Furthermore, the fact that patients of different racial groups have different mortality outcomes in the simulation, despite the absence of the race as a factor in the resource allocation prioritization algorithm, suggests that the SRAP as currently designed may perpetuate or even exacerbate existing disparities in mortality.

The amount of the expired fraction data explained by the proposed models is relatively small as noted by the adjusted R^2, ranging from 0.05 to 0.12. Interestingly, the models that disaggregated the Triage Category into its component parts, specifically the uSOFA score and the presence of prespecified comorbidities, tend to explain more of the simulated data. This suggests that the summarization of the Policy Criteria into the Triage Category may involve a loss of information associated with reduced ability to predict mortality.

The use of the Comorbidity Component in place of individual comorbidities appears to also have led to loss of information. In models 2 and 5, we found that the same three comorbidities – end stage renal disease on dialysis; severe chronic lung disease with FEV1 less than 20 percent predicted, FVC less than 35 percent predicted, or in the absence of pulmonary function tests (PFTs), chronic home oxygen at rest of mechanical ventilation; and metastatic cancer with expected survival less than or equal to 1 year despite treatment *or* refractory hematologic malignancy (resistant or progressive despite conventional initial therapy) – were significant predictors of increasing risk of mortality. Interestingly, cirrhosis with a MELD greater than or equal to 20, prevalent in 10 percent of the encounters, was not associated with any increased mortality risk even in the setting of no constraint, yet the SRAP uses it to deprioritize patients, possibly increasing their risk of mortality when constraints are applied. In models 1 and

4, where these comorbidities are collapsed into the Comorbidity Component, the impact of the

SOFA Component (effectively the uSOFA score) on mortality increases. This is potentially

problematic given recent research on disparities related to SOFA use, which will be explored in

the next chapter of this dissertation.

Finally, our results identify patients most at risk of unexpected mortality because of

resource allocation policies. The Green patients that appear in the charts reflecting constraint

became Green *after* they expired in the simulated constraint scenarios, which only happened if

the patient was removed from an ICU bed and did not return within one day. This means that

they were known to have survived in the base case, and thus would not have died except for the

implementation of the Policy related to the constraint imposed. This knowledge calls for further

study of patient or policy factors to assess if the Policy may be inadvertently withdrawing

resources from patients who are likely to survive.

Implications

To our knowledge, this is the first study to examine the impact of a published scarce resource

allocation policy as written on a real-world patient population. To date, the literature reviewing

implementation of existing policies have largely stopped short of outcomes, instead highlighting

disparities in prioritization across various patient demographics (e.g., age, race). Additionally,

previous studies have either been limited in the scope of their resource concerns (e.g., only

ventilators) or lacked real-world data.

Our study offers insight into the feasibility of operationalizing an allocation policy. In our

study that allocated priority prospectively, as would happen in actual implementation, the

missingness of data was minimal – of 974 patients admitted to the ICUs over the study period,

only 11 patients (1.1 percent) had to be excluded from simulation and analysis due to missing

priority scoring data. In the Riviello study, the authors note that data was missing for

approximately 18 percent of patients in the study period, likely due to retrospective collection.

Our study limited assumptions to practical considerations in implementation. The "all-or-nothing" assumption reflects standard practices in that patients who require intensive monitoring by limitation of personnel or facilities must move to an ICU. Even when critical care is moved physically outside of the ICU, this effectively increases the number of available "ICU" beds. Our simulation study methods allow for any assumptions to be easily adjusted, enabling others to assess for robustness of conclusions to any degree of change.

As the base case simulation represents application of the SRAP without any actual changes in resource allocation, this scenario offers valuable insight into the Policy's ability to identify clinical factors associated with higher mortality. The *expired fraction* variable only takes on the values 0 and 1 because, in the base case scenario, only patients who were known to have died during the study period transitioned to the Expired state. Thus, the coefficients from the univariate and multivariate regressions in the base case describe associations between the selected variables and mortality in the observed population. Finally, our results are supported by their foundation in historical data, as the only assumptions of mortality outside the non-allocation mortality clock were based on observed deaths in the study sample.

Limitations

As many studies that precede ours, our findings are limited by the fact that the input data is derived from a single quaternary care academic institution, and thus conclusions about the implementation of the policy should be cautiously extrapolated. The population represented in the pilot study is noticeably different from the surrounding Los Angeles County.[44]

Systematically missing data may have affected the results. Data was collected in a hierarchical manner such that only data necessary at a given point in the triage algorithm was collected at that time. As the Triage Categories Violet, Blue, and Green did not require the collection of SOFA and Comorbidity Components, observations reflecting such triage encounters would be missing data for all those variables. These patients were excluded from

regression analyses examining the impact of these variables on mortality. Additionally, an individual patient could be assigned a new Triage Category on subsequent study days during which SOFA and Comorbidity Component data would be collected. Given this operationalization of the Policy within the medical record tool and data collection method, statistical analytical methods accounting for clustered data at the patient level (with multiple observations per patient) would have been ideal. We attempted to create such models with generalized linear models, using the gaussian distribution for the *expired fraction* outcome and the Poisson distribution for the *expired counts* outcome, but could not generate models that converged. This is likely because, while the number of clusters (patients) was sufficiently large, the number of observations per patient was low for some patients.

In addition, the conclusions drawn around the non-allocation mortality clock assumption are limited in generalizability in that the sensitivity analysis effectively used a Bernoulli distribution for mortality, such that p_{OD} was 0 until the Final State was "Out" and the number of cycles in the "Out" state was equal to the simulation variable *dc*, at which point p_{OD} became 1. This implies that all patients in the simulation have the same probability of survival without critical care, regardless of their acuity of illness or comorbid conditions. Given that both factors are expected to impact mortality, more robust sensitivity analyses allowing for greater variation in this probability are indicated to test the validity of this assumption, ideally incorporating those factors into the probability function.

The ability to conduct sensitivity analyses was further limited by the nature of the input data – since Triage Category was determined prior to simulation, it was not possible to determine the impact of specific Policy Criteria on mortality outcomes. In future work, the determination of Triage Category as a function of Policy Criteria (and Patient Characteristics) could be incorporated into the programming to allow investigators to simulate outcomes with factors differently weighted or omitted.

Chapter 4: Analyzing the Role of Policy Criteria in Allocation and Mortality Disparities Among Racial Groups Using Mediation Methods

Background and Hypotheses

Racial Disparities in Chronic Disease

The Policy studied in this dissertation, like many of the publicly available proposed resource allocation policies, relies on the assessment of presence of several chronic conditions as a surrogate for estimating likelihood of longer-term survival. As mentioned in the introductory chapter, this strategy has the potential to introduce bias into the algorithm for determining allocation priority. By using factors highly correlated with an unmeasured attribute (in this case, race), such allocation algorithms might perpetuate existing racial disparities. Medical and public health literature is replete with publications that describe differences in the prevalence of, as well as disparities in outcomes related to, several of the prespecified comorbidities utilized in the UC SRAP. Miller and colleagues recently argued that the use of such comorbidities is likely to exacerbate disparities in health care, citing in particular the large difference in prevalence of end-stage renal disease in black and Latino patients compared to White patients.[45]

Chronic kidney disease (CKD) is well-documented as one of these comorbidities for which significant differences exist when considering prevalence among various racial groups. Using life-table methods to estimate lifetime risk of ESRD based on surveillance data from the United States Renal Data System (USRDS), Albertus and colleagues documented a greater than 2.5-fold increase in the lifetime risk of ESRD among non-Hispanic Black males compared to non-Hispanic White males, and a 3.3-fold increase in the lifetime risk among the female counterparts.[46] The latest annual data report from USRDS stated that increase in ESRD prevalence was highest in Black patients among all racial groups, and prevalence of ESRD in Black patients was approximately double that in Hispanic patients, triple that in Asian patients, and nearly quadruple that in White patients.[47]

Among the major comorbidities used in the UC SRAP, chronic obstructive pulmonary disease (COPD) has also been shown to disproportionately affect one racial group over others. As recently as 2018, COPD continues to remain more prevalent among non-Hispanic White patients, according to an analysis conducted by the American Lung Association based on National Health Interview Survey (NHIS) data. As of 2020, COPD mortality was also highest among non-Hispanic White patients, based on an analysis conducted using the Center for Disease Control and Prevention (CDC) Underlying Cause of Death database.[48,49]

Among the severely life-limiting comorbidities specified by the UC SRAP, the literature describes well-known disparities in the burden of cancer among several minority groups compared to White patients. The National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) Program shows that, while cancer incidence and mortality have generally improved over the past several decades, disparities in both measures exists among racial groups. In particular, non-Hispanic African American men continue to have the highest incidence of and mortality from cancer across all cancer types.[50] Researchers have studied the mechanisms underlying both the disproportionate rates of diagnosis and deaths from cancer among racial groups, and recent literature has emphasized the contribution of an individual's socioeconomic status and healthcare system factors to the creation of disparities in access to cancer care and cancer mortality.[51,52]

Disparities in the allocation of resources and care to patients with cirrhosis, represented in both the major and severely life-limiting comorbidity lists, should also be mentioned given the relatively high prevalence in our population (Table 21). One review in the hepatology literature found that Hispanic patients have a higher prevalence of non-alcoholic fatty liver disease and alcoholic cirrhosis, higher incidence of complications chronic liver disease including hepatocellular carcinoma, and lower response to treatment for hepatitis C, which itself is a risk factor for cirrhosis.[53] A more recent retrospective cross-sectional analysis of National Inpatient Sample data from 2009-2018 found a persistence in resource allocation and mortality disparities

by race. Over the course of the study, Black and Hispanic patients remained less likely to receive a liver transplant than White patients, and mortality from cirrhosis remained significantly higher among Black patients compared to White patients.[54]

These examples illustrate how the presence of certain diagnoses might reflect the history of inequities in our healthcare system with regards to the increased risk of chronic illness for minority populations. Using these comorbidities to determine the allocation of resources in the acute setting carries the risk of perpetuating the existing racial disparities observed in the outcomes related to these conditions. Since policies such as the SRAP rely solely on the presence of such comorbidities, not the risk of mortality associated with such conditions, in determining priority for resource allocation, it is possible that such criteria might serve as a proxy for race, thereby leading to disparities in ICU mortality.

Racial Bias in Measures of Acute Illness

As do many of the resource allocation policies proposed in the setting of the COVID-19 pandemic, the UC SRAP relies on the SOFA score as an "objective measure of acute illness severity." Latest literature suggests, however, that this score may not be unbiased with respect to race. Based on an earlier retrospective study by Raschke et. al. that showed the SOFA score to be poorly predictive of mortality in COVID-19 patients, Tolchin and colleagues performed a retrospective analysis of more than 2300 patients across a single hospital system examining disparities in SOFA scores at the time of triage and found that non-Hispanic Black patients, but not Hispanic patients, had lower SOFA scores at time of triage compared to White patients.[55,56] While their study was limited to a single disease population as well as to one hospital system, the authors raised concern that such differences could lead to policies that rely on the SOFA score "would be more likely to deny non-Hispanic Black patients scarce medical resources such as ventilators and ICU beds."

Miller and colleagues, contemporary to their work cited above, studied 111,885 ICU encounters representing more than 95,000 patients in the eICU Collaborative Research

Database, a multicenter, nationally representative database of ICU admissions representing three unique levels of data (patient, hospital, unit).[57] Building on the study by Tolchin, this study compared the SOFA scores at the time of triage to observed mortality. In doing so, the authors found that mortality was, on average, lower for Black patients with a given SOFA score, compared to White patients.[58] Their findings suggest that the SOFA score may be biased in its estimation of mortality for Black patients, further raising the concern that its use would lead to systematic de-prioritization of resources under crisis standards of care policies aimed at maximizing the number of lives saved.

Conceptual Model

The conceptual framework presented earlier in this dissertation is shown below in Figure 21, modified to highlight the specific aims of this chapter. The solid arrows in the figure highlight pathways implied by the policymakers – by selecting for lower SOFA and Comorbidity Components, the policy determines a Triage Category, which in turn optimizes (minimizes) mortality. The dotted arrows identify pathways to be explored in the analyses in this chapter. In particular, we ask whether disparities in measurements of acute illness (SOFA Component) and experiences with chronic illness (Comorbidity Component) propagate or compound disparities in allocation decisions and mortality. Given the concerns raised with the use of SOFA scores and certain comorbidities in resource allocation policies with regards to racial disparities, we focus on race among the Patient Characteristics and the potential for differences in race to be mediated by the SOFA and Comorbidities components of the UC SRAP. The dashed arrow represents unidentified relationships between other Patient Characteristics and Policy Criteria.
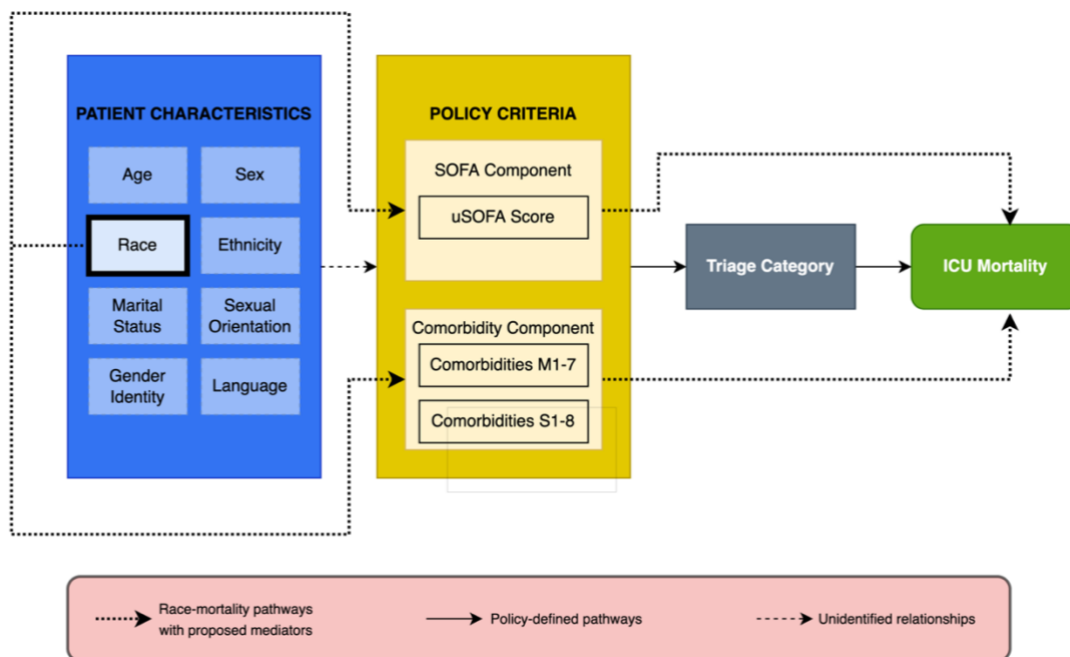
Figure 21: Conceptual model identifying potential race-mediated pathways

Acknowledging that there are many ways of modeling mediation, in this chapter, we explore mediation by measuring how the risk of mortality by might influenced by race through the use of the SOFA Component or the Comorbidity Component. By modeling the impact of race on mortality with and without these components, we measure these "indirect" effects to determine if they are statistically significant contributors to the risk of mortality.

Methods

Data Collection and Preparation

The simulation results from the prior chapter provide the data for the analyses presented in this chapter. No further modifications to the dataset were necessary for the analyses described.

Key Variables and Definitions

In this chapter, we consider the Policy Criteria variables *SOFA Component* and *Comorbidity Component* as potential mediators. We focus on the Patient Characteristics variable *race* as the exposure variable. Mortality is represented by the continuous outcome variable *expired fraction*. These variables are summarized in Table 29. Triage Category is included as a mediator

variable, but as it is directly determined by the Triage Score, which itself is defined by a combination of the SOFA Component and the Comorbidity Component, it is omitted from the models given expected collinearity with the latter two variables.

Table 29: Summary of Exposure, Mediator, and Outcome Variables

	Variable	Type	Values
Outcome	*Mortality*		
	Expired fraction	Continuous	0 – 1
Exposure	*Patient Characteristic*		
	Race	Categorical	White or Caucasian, Black or African American (AA), Asian, Native Hawaiian or Other Pacific Islander (NH/PI), Middle Eastern or North African (ME/NA), American Indian or Alaska Native (AI/AN), Do Not Identify, Other, Unknown
Mediator	*Policy Criteria*		
	SOFA Component	Integer	1 – 4
	Comorbidity Component	Nominal	0, 2 (if any present from Comorbidities M1-7), 4 (if any present from Comorbidities S1-7), Unknown/Unavailable
	Triage Category	Categorical	Violet, Red, Orange, Yellow, Blue, Green

Statistical Analysis

We began our analysis by exploring differences in the distribution of the mortality variable *expired fraction* among the different racial groups. As the data was not normally distributed, we compared the median values of expired fraction for each racial group. To determine statistical significance in any differences, we performed the Kruskal-Wallis test between *expired fraction* and *race* to determine if there existed any difference among the median values in the outcome among the groups. We repeated this analysis across constraint levels to examine the possibility that these associations might be moderated by strain on available resources.

Turning to the mediator variables, we generated contingency tables between the variable *race* and each of the Policy Criteria variables *SOFA Component*, *Comorbidity Component*, and *Triage Category*. These proportions were calculated along the row dimension, such that each cell represented the proportion of a racial group within a given level of the Policy Criteria variable. We then performed Fisher's exact test to determine if there was an association

between membership in a racial group and the Policy Criteria variables. A p-value of 0.05 or less was considered statistically significant.

Finally, we determined degree of mediation by defining nested linear regression models. For each Policy Criteria variable, we defined a total effect model with *expired fraction* as the outcome and *race* (as well as the other identified Patient Characteristics variables) as the exposure variables. For the *race* variable, 'White or Caucasian' was used as the reference level. We defined a direct effect model with *expired fraction* as the dependent variable, now including the individual Policy Criteria variable among the independent variables. We extracted the coefficients from these models and determined the indirect effect of race, which represents the effect mediated by the Policy Criteria variable, as the difference between the coefficients in the total effect model and the coefficients in the direct effect model. Figure 22 shows the mediation pathways from the overarching framework explored in this analysis. The total and direct effects of race on mortality (c_{rm} and c'_{rm}, respectively) are represented by the coefficients from the corresponding models. The indirect effect of race on mortality is represented by the product of individual mediating effects in each pathway – c_{rs} *c_{sm} for the SOFA Component, and c_{rc}*c_{cm} for the Comorbidity Component.
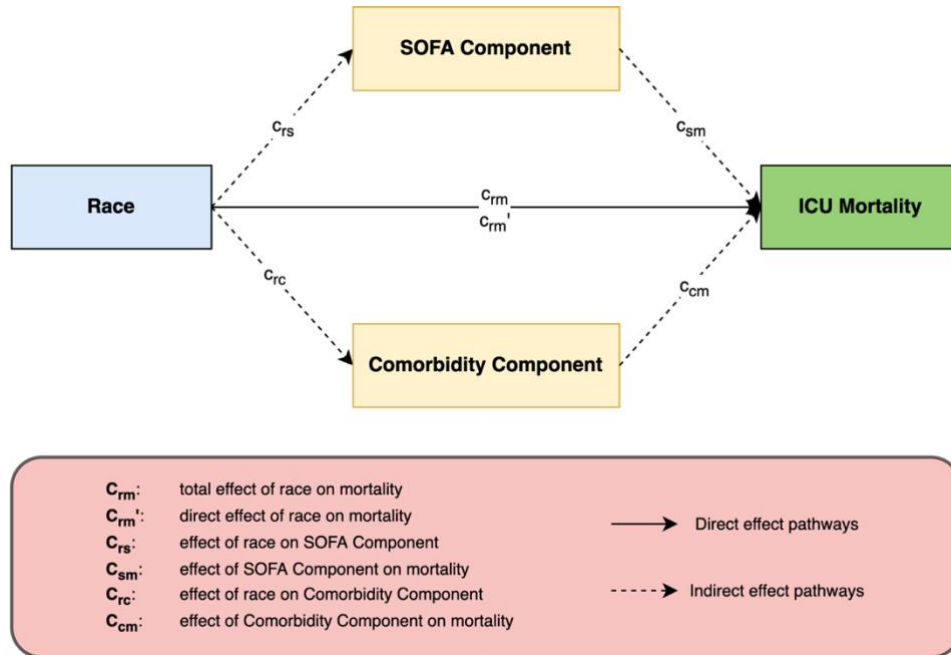
Figure 22: Mediation diagram depicting direct and indirect effects of race on mortality through Policy Criteria variables

We used the original dataset from the previous microsimulation analysis to determine

the population level total, direct, and indirect effects of race on mortality. To calculate the

confidence intervals around the indirect effects, we performed bootstrapping analyses in which

we sampled with replacement 963 observations from the original dataset, using the sampled

dataset to perform the regressions described above. We repeated this process 1000 times,

extracting the coefficients for each racial group and subtracting the direct effect coefficient from

the total effect coefficient each time. We analyzed the summary statistics for the bootstrapped

set of coefficients to determine the standard error. The 95% confidence intervals for the indirect

effects were then calculated by adding and subtracting 1.96 times the standard error to the

indirect effect coefficients.

All analyses were conducted in R.[35]

Results

Racial Differences in Mortality Risk and Policy Criteria

The summary of the distribution of *expired fraction* for each racial group under the specified constraint levels is shown in Table 30. The Kruskal-Wallis test for *expired fraction* grouped by *race* under each constraint level was statistically significant with all four test statistics having p values less than 0.001. Given this result, we performed pairwise Wilcoxon rank sum testing for expired fraction between each race and White or Caucasian as reference. The proportion of each Triage Category within each racial group is shown in Table 31. The results of Fisher's exact test suggest that the composition of Triage Categories represented in each of the 10 identified racial groups differ significantly. Table 32 shows the proportion of each SOFA Component score present in each racial group. Again, the results of Fisher's exact test suggest that the difference in these compositions across race are statistically significant. Table 33 similarly shows the proportion of each Comorbidity Component value present in each racial group. Again, these compositions differ significantly based on the results of Fisher's exact test.

Table 30: Distribution statistics of expired fraction by racial group and constraint level

Race	N	Base			Moderate			Severe			Extreme		
		Mean	Median	IQR	Mean	Median	IQR	Mean	Median	IQR	Mean	Median	IQR
White or Caucasian	405	0.03	0	(0, 0)	0.105	0	(0, 0)	0.175	0	(0, 0.162)	0.219	0	(0, 0.343)
Black/AA	103	0.03	0	(0, 0)	0.112	0	(0, 0)	0.202	0	(0, 0.232)	0.257	0.051	(0, 0.445)
AI/AN	2	0	0	(0, 0)	0.002	0.002	(0.001, 0.002)	0.075	0.075	(0.038, 0.113)	0.018	0.018	(0.009, 0.027)
Asian	81	0.074	0***	(0, 0)	0.12	0	(0, 0)	0.211	0	(0, 0.191)	0.272	0.003	(0, 0.521)
ME/NA	17	0	0	(0, 0)	0.035	0	(0, 0)	0.165	0	(0, 0.207)	0.231	0	(0, 0.279)
NH/PI	5	0.2	0	(0, 0)	0.396	0***	(0, 0.982)	0.464	0.321***	(0, 1)	0.526	0.628***	(0, 1)
Multiple Races	28	0	0	(0, 0)	0.017	0***	(0, 0)	0.073	0***	(0, 0.042)	0.132	0***	(0, 0.167)
Do Not Identify	17	0	0	(0, 0)	0.112	0	(0, 0)	0.168	0	(0, 0.001)	0.181	0	(0, 0.053)
Other	245	0.037	0***	(0, 0)	0.12	0	(0, 0.001)	0.207	0***	(0, 0.264)	0.271	0.043***	(0, 0.57)
Unknown	60	0	0	(0, 0)	0.045	0***	(0, 0)	0.111	0	(0, 0.046)	0.16	0*	(0, 0.221)

Results of Wilcoxon rank sum testing of difference in expired fraction distribution (compared to White or Caucasian): *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 31: Triage Category Distribution in all Triage Encounters by Race

Race	N	Triage Category (Proportion of *N*)					
		Violet	Red	Orange	Yellow	Blue	Green
White or Caucasian	1454	0.188	0.196	0.151	0.175	0.017	0.272
Black or AA	390	0.118	0.246	0.133	0.2	0.036	0.267
AI/AN	5	0	0	0	0.4	0	0.6
Asian	275	0.222	0.284	0.087	0.156	0.011	0.24
ME/NA	69	0.217	0.232	0.174	0.087	0	0.29
NH/PI	33	0	0	0.212	0.667	0	0.121
Multiple Races	75	0.173	0.187	0.16	0.08	0	0.4
Do Not Identify	87	0.287	0.276	0.092	0.103	0	0.241
Other	1027	0.118	0.210	0.107	0.282	0.019	0.263
Unknown	211	0.308	0.19	0.161	0.057	0	0.284

Fisher's exact test: $p < 0.001$

Table 32: SOFA Component Distribution in all Triage Encounters by Race

Race	N	SOFA Component (Proportion of *N*)			
		1	2	3	4
White or Caucasian	1454	0.375	0.319	0.161	0.145
Black or AA	390	0.302	0.391	0.115	0.191
AI/AN	5	0.333	0	0	0.667
Asian	275	0.322	0.377	0.199	0.103
ME/NA	69	0.676	0.235	0.088	0
NH/PI	33	0.172	0.724	0.103	0
Multiple Races	75	0.343	0.229	0.257	0.171
Do Not Identify	87	0.326	0.512	0.116	0.047
Other	1027	0.253	0.333	0.199	0.215
Unknown	211	0.544	0.233	0.144	0.078

Fisher's exact test: $p < 0.001$

Table 33: Comorbidity Component Distribution in all Triage Encounters by Race

Race	N	Comorbidity Component (Proportion of *N*)			
		0	**2**	**4**	**Unknown/ Unavailable**
White or Caucasian	1454	0.319	0.172	0.494	0.015
Black or AA	390	0.455	0.123	0.417	0.004
AI/AN	5	0	0.333	0.667	0
Asian	275	0.466	0.219	0.288	0.027
ME/NA	69	0.324	0.176	0.471	0.029
NH/PI	33	0	0.069	0.931	0
Multiple Races	75	0.486	0.286	0.229	0
Do Not Identify	87	0.535	0.116	0.326	0.023
Other	1027	0.317	0.124	0.54	0.019
Unknown	211	0.367	0.189	0.4	0.044

Fisher's exact test: $p < 0.001$

Mediation of Race Effects by SOFA

The results of the mediation analysis for the SOFA Component are shown below. Table 34 shows the total effect as determined by the linear regression model including only the Patient Characteristics variables and the direct effect as determined by the model that incorporates the SOFA Component. In the base case of no resource constraint, the total and direct effects of race appeared to be significant for patients who identified as Asian (compared to patients identifying as White or Caucasian), but these effects were no longer statistically significant under any level of constraint. The results for Native Hawaiian or Other Pacific Islander patients compared to White patients should be interpreted with extreme caution, given the very small number of patients present in our study sample that may very well not be representative because of overspecification. Keeping this in mind, the total effect of race was significant under no constraint and moderate constraint but not under severe or extreme constraint. For these patients, the direct effect of race with respect to the SOFA Component became significant under moderate constraint and persisted under severe and extreme constraint levels.

For all racial groups under all constraint levels (compared to White patients), the effect of race mediated by the SOFA component was statistically insignificant, as shown by each of the bootstrapped 95 percent confidence intervals in Table 35. While these effects did not meet thresholds for significance, it is worth noting the wide range of magnitudes for the degree of mediation among the racial groups within a given constraint level. Even within the base case, for which actual outcomes were known, the percent mediation ranged from -1001.8 percent for patients identifying as Other to 27.7 percent for patients identifying as Middle Eastern or North African. The latter were the only group to have a positive mediation effect, while the remainder showed varying amounts of suppression and reversal of effect of race by SOFA score.

The change in degree to which race was mediated by SOFA across constraint levels was not uniform among the groups. For patients identifying as Asian, the percent mediation remained negative and greater than 100 across constraint levels, suggesting that SOFA

83

suppressed and reversed the effect of race compared to White patients. This was not the case for Black or African American patients, for whom SOFA appeared to suppress but no longer reverse the effect of race under any level of constraint. Compared to White patients, for patients identifying as Native Hawaiian or Other Pacific Islander, SOFA appeared to reverse but not suppress the direct effect of race. Again, the reproducibility of these results should be questioned given the extremely small sample size in our population.

Direct and indirect effects of race with respect to the SOFA Component could not be determined for American Indian or Alaska Native patients as their representative observations in the dataset did not include SOFA scores.

Mediation of Race Effects by Comorbidities

The results of the mediation analysis for the Comorbidity Component are shown in Table 36 and Table 37. Table 36 shows the total effect as determined by the linear regression model including only the Patient Characteristics variables, which as expected is identical to the Total columns in Table 34. The direct effect was determined by the model that incorporates the Comorbidity Component to the total effect model. Curiously, the direct effect of race was again statistically significant for Asian patients under extreme constraint.

Once again, for all racial groups under all constraint levels, the effect of race mediated by the Comorbidity component did not meet thresholds for statistical significance, as shown by each of the bootstrapped 95 percent confidence intervals in Table 37. It is again worth noting the wide range of magnitudes for the degree of mediation among the racial groups within a given constraint level despite the lack of statistical significance. In the base case, the percent mediation ranged from -1459.9 percent for patients identifying as Other to -28 percent for patients whose race was unknown. While the range was slightly wider, it appears that the Comorbidity Component uniformly suppressed and reversed the effect of race in the base case. While the mediation patterns for the Comorbidity Component were similar to those for the SOFA Component for Asian and Black or African American patients compared to White patients, there

were slightly new patterns seen for Middle Eastern or North African and Native Hawaiian or Other Pacific Islander patients. Compared to White patients, comorbidities appeared to counter but not fully reverse the effect of race for Middle Eastern or North African Patients in the base case. For Native Hawaiian or Other Pacific Islander patients, we observed positive mediation under moderate and severe constraints compared to the SOFA Component.

As in the case of the SOFA Component analysis, the direct and indirect effects of race with respect to the Comorbidity Component could not be determined for patients identifying as American Indian or Alaska Native as the dataset observations corresponding to these patients did not include comorbidity data.

Table 34: Total and direct effect coefficients of race on risk of mortality and proportion mediated by SOFA Component by constraint level

Race	Base			Moderate			Severe			Extreme		
	Total	Direct	Mediation (%)	Total	Direct	Mediation (%)	Total	Direct	Mediation (%)	Total	Direct	Mediation (%)
White or Caucasian	Reference											
Black or AA	0.006	0.017	-190.8	0.004	-0.044	1271.1	0.032	-0.029	189.9	0.044	-0.025	156.2
AI/AN	-0.02	NC	NC	-0.075	NC	NC	-0.008	NC	NC	-0.162	NC	NC
Asian	0.05*	0.104**	-110.1	0.008	0.02	-160.8	0.026	0.054	-109.2	0.047	0.106	-129.1
ME/NA	-0.027	-0.02	27.7	-0.075	-0.071	5.23	-0.006	0.034	652.3	0.019	0.09	-363.5
NH/PI	0.174*	0.315	-80.7	0.282*	0.485**	-72.3	0.288*	0.473*	-64.1	0.297	0.497*	-67.5
Multiple Races	-0.025	-0.029	-15.2	-0.091	-0.148	-62.5	-0.098	-0.109	-12.6	-0.09	-0.049	45.3
Do Not Identify	-0.048	-0.066	-38.9	-0.031	0.129	519.8	-0.061	0.146	339.6	-0.111	0.047	142.8
Other	0.001	0.013	-1001.8	-0.014	-0.002	87.4	-0.017	-0.025	-42.1	-0.006	0	100
Unknown	-0.036	-0.038	-6.99	-0.066	-0.052	21.0	-0.074	-0.076	-3.27	-0.083	-0.092	-11.1

* p < 0.05; ** p < 0.01; *** p < 0.001
NC: not calculated

Table 35: Indirect (mediated) effect of race on risk of mortality by constraint level, SOFA Component

Race	Base		Moderate		Severe		Extreme	
	Coefficient	95% CI	Coefficient	95% CI	Coefficient	95% CI	Coefficient	95% CI
White or Caucasian	Reference							
Black or AA	-0.011	(-0.085, 0.063)	0.048	(-0.061, 0.157)	0.061	(-0.12, 0.242)	0.069	(-0.121,0.259)
AI/AN	NC	NC	NC	NC	NC	NC	NC	NC
Asian	-0.055	(-0.261, 0.152)	-0.013	(-0.283, 0.258)	-0.028	(-0.328, 0.271)	-0.06	(-0.383, 0.262)
ME/NA	-0.007	(-0.578, 0.563)	-0.004	(-0.735, 0.728)	-0.04	(-0.571, 0.491)	-0.071	(-0.534, 0.392)
NH/PI	0.141	(-0.747, 0.466)	-0.204	(-1.10, 0.69)	-0.185	(-0.986, 0.616)	-0.2	(-0.993, 0.593)
Multiple Races	0.004	(-0.072, 0.079)	0.057	(-0.375, 0.489)	0.012	(-0.444, 0.469)	-0.041	(-0.425, 0.343)
Do Not Identify	0.018	(-0.182, 0.219)	-0.159	(-0.437, 0.119)	-0.207	(-0.48, 0.065)	-0.217	(-0.489, 0.054)
Other	-0.011	(-0.271, 0.247)	-0.012	(-0.368, 0.344)	0.007	(-0.36, 0.374)	0.009	(-0.213, 0.232)
Unknown	-0.003	(-0.072, 0.077)	-0.014	(-0.145, 0.118)	0.002	(-0.193, 0.198)	-0.083	(-0.312, 0.147)

NC: not calculated

Table 36: Total and direct effect coefficients of race on risk of mortality and proportion mediated by Comorbidity Component by constraint level

Race	Base			Moderate			Severe			Extreme		
	Total	Direct	Mediation (%)	Total	Direct	Mediation (%)	Total	Direct	Mediation (%)	Total	Direct	Mediation (%)
White or Caucasian	Reference											
Black or AA	0.006	0.018	-206.2	0.004	-0.036	1046.8	0.032	-0.026	179.7	0.044	-0.026	159.2
AI/AN	-0.02	NC	NC	-0.075	NC	NC	-0.008	NC	NC	-0.162	NC	NC
Asian	0.05*	0.115**	-130.9	0.008	0.074	-851.8	0.026	0.107	-313.9	0.047	0.14*	-199.8
ME/NA	-0.027	-0.035	-31.0	-0.075	-0.069	7.48	-0.006	0.012	295.7	0.019	0.058	-198.1
NH/PI	0.174*	0.273*	-56.6	0.282*	0.246	12.6	0.288*	0.259	10.0	0.297	0.377	-26.9
Multiple Races	-0.025	-0.034	-33.6	-0.091	-0.118	-29.3	-0.098	-0.121	-24.0	-0.09	-0.081	10.4
Do Not Identify	-0.048	-0.079	-65.4	-0.031	0.062	302.3	-0.061	0.088	243.6	-0.111	0.014	112.8
Other	0.001	0.019	-1459.9	-0.014	0.018	236.5	-0.017	0.009	151.7	-0.006	0.028	573.5
Unknown	-0.036	-0.046	-28.2	-0.066	-0.046	29.2	-0.074	-0.067	8.7	-0.083	-0.088	-5.5

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
NC: not calculated

Table 37: Indirect (mediated) effect of race on risk of mortality by constraint level, Comorbidity Component

Race	Base		Moderate		Severe		Extreme	
	Coefficient	95% CI	Coefficient	95% CI	Coefficient	95% CI	Coefficient	95% CI
White or Caucasian	Reference							
Black or AA	-0.012	(-0.079, 0.055)	0.039	(-0.069, 0.148)	0.058	(-0.122, 0.237)	0.07	(-0.124, 0.264)
AI/AN	NC	NC	NC	NC	NC	NC	NC	NC
Asian	-0.065	(-0.191, 0.062)	-0.067	(-0.226, 0.092)	-0.081	(-0.24, 0.077)	-0.093	(-0.362, 0.176)
ME/NA	0.008	(-0.053, 0.07)	-0.006	(-0.197, 0.186)	-0.018	(-0.233, 0.196)	-0.038	(-0.293, 0.216)
NH/PI	-0.098	(-0.683, 0.487)	0.035	(-0.589, 0.66)	0.029	(-0.412, 0.47)	-0.08	(-0.387, 0.228)
Multiple Races	0.008	(-0.068, 0.085)	0.027	(-0.119, 0.173)	0.023	(-0.217, 0.264)	-0.009	(-0.284, 0.266)
Do Not Identify	0.031	(-0.075, 0.137)	-0.093	(-0.46, 0.275)	-0.149	(-0.576, 0.278)	-0.125	(-0.543, 0.294)
Other	-0.017	(-0.087, 0.053)	-0.032	(-0.123, 0.059)	-0.026	(-0.139, 0.086)	-0.034	(-0.151, 0.082)
Unknown	0.01	(-0.396, 0.417)	-0.019	(-0.539, 0.5)	-0.006	(-0.495, 0.483)	0.005	(-0.5, 0.509)

NC: not calculated

Discussion

The results of this chapter suggest that the impact of race on mortality is not significantly propagated by the SOFA Component of the SRAP, all other Patient Characteristic variables held constant. Similarly, race does not appear to be significantly mediated by the Comorbidity Component in its effect on mortality risk, holding all other Patient Characteristic variables constant. While our results did not meet thresholds for statistical significance, the suggested magnitude of the mediation effects and the variation across constraint levels suggest that there may be more complex interactions between race, severity of acute illness, presence of chronic medical conditions, degree of resource constraint, and risk of mortality.

Methodologic issues that may explain this outcome include the inability to generate models based on clustered data as discussed in the previous chapter. In condensing the dataset to a single observation per patient, it is possible that information about SOFA scores and comorbidities were discarded. As mentioned in the microsimulation chapter, the use of linear models required a single observation per patient, and for 98 of the 963 patients in the sample, this meant relying on an observation for which the Triage Category was not the same as the subsequent Triage Categories for the patient. However, it was only the case in 2 of the patients that this reliance on the first observation resulted in a loss of SOFA and/or Comorbidity Component data, so this is unlikely to have significantly impacted our results.

Misspecification of racial groups is most likely contributing to our inconsistent findings. Of the patients who identified as 'Other," almost half (47.7 percent) identified as Hispanic or Latino ethnicity, but 36.7 percent identified as Not Hispanic or Latino and 15 percent identified their ethnicity as 'Other,' suggesting that this racial group was quite heterogenous. Similarly, in the patients of Unknown race, more than half (52.6 percent) identified as Hispanic or Latino. This suggests that some combination of race and ethnicity may be necessary to better identify

how these specific patient characteristics are associated with allocation priority and subsequent risk of mortality.

Implications

This analysis is the first to our knowledge to comprehensively examine the relationship between patient factors, policy criteria, and expected outcomes of implementation of a scarce resource allocation policy under crisis standards of care. Prior work, as previously discussed, has provided evidence of a relationship between race, the SOFA score, and specific chronic conditions. Our work further explores these relationships and offers insight into the relative contribution of race to allocation and mortality outcomes.

The methodology demonstrated here provides a framework for assessing mediation of other clinical factors currently absent from the UC SRAP and most other published policies, such as age, which will be discussed in the concluding chapter. Such clinical factors are used routinely in practice to ascertain a patient's risk of having a specific medical condition or of succumbing to acute illness. The framework in Figure 22 can be modified such that race can be substituted for any Patient Characteristic variable for which data is available to determine how the effects of these variables on risk of mortality under varying constraint levels may be mediated by certain Policy Criteria variables. Similarly, the Comorbidity Component can be substituted for individual comorbid conditions to determine how, if at all, the effects of Patient Characteristics may be mediated by particular comorbidities.

Limitations

The analyses conducted are limited by the data collection strategy in the original study. Since SOFA scores and presence of comorbidities were not collected for Violet, Blue, and Green patients, the direct effect models provide regression coefficients based on data not missing at random. This would be expected to introduce bias in the coefficients for *SOFA Component* and *Comorbidity Component*, which would be reflected in the indirect effects of the *race* variable.

This bias could occur in either direction. Patients in the Blue category, who are given lowest priority for critical care resources due to a catastrophic condition, might be severely chronically ill leading to refractory cardiac arrest, or might have been perfectly healthy until a traumatic event leading to a comatose state. These two patients are evaluated similarly by the policy in that the catastrophic condition is assessed first, and the presence or absence of comorbid conditions would not have been ascertained. Similarly, while the SOFA scores were automatically calculated in the medical record, the Triage Allocation Tool did not file these scores unless a Triage Category requiring the incorporation of these data were filed.

Additionally, the models proposed here rely on assumptions of linearity that are not fully met by the data. While the mean and median of the residuals for both the total effect and direct models were very close to 0, they were not exactly equal, suggesting slight skew and therefore asymmetric and non-normal distributions.

Finally, the racial composition of our study population and the prevalence of specific comorbidities limits the external validity of our results. As suggested by the number of patients and the number of triage encounters for each group in Table 30 and Table 31, respectively, several groups were substantially underrepresented relative to other groups in the sample. As Table 21 shows, several comorbidities are relatively rare in our population. Given that the presence of any one of these conditions would increase the Triage Allocation Score by at least 2 points, significant difference in another population would deterministically lead to differences in distribution of Triage Categories. This would in turn potentially lead to changes in risk of mortality (as represented by each patient's *expired fraction* value) and alternative conclusions about associations between this race, risk of mortality, and the degree to which that is mediated by policy criteria.

Chapter 5: Discussion on Future Research in Scarce Resource Allocation Policy Development

Summary of Work

Our research shows that there is significant work to be done before widespread adoption and implementation of research allocation policies like the UC SRAP. The rapid proliferation of these policies during the COVID-19 pandemic has been quickly followed by research raising substantial issues with the potential for exacerbation of disparities. This dissertation reiterates those concerns, in addition to raising new alarms related to the reliability of such policies. While this work could not establish an association of disagreement in allocation priority with mortality outcomes or racial disparities, the presence of such disagreement should give pause given the demonstrated association of lower Triage Category with risk of mortality. Acknowledging the limitations discussed within each of the analytical chapter, we demonstrate that the UC SRAP may not meet the hypothesized goal of preserving cohort mortality at baseline levels. While these analyses did not compare the SRAP to continuing current care, and therefore do not suggest that the SRAP is worse than no policy, this dissertation provides evidence that triage as protocolized by the SRAP is insufficient to maintain mortality at pre-constraint levels.

Improving Interrater Reliability of Policies

The reliability analyses presented here are impactful in their consideration of individual elements of the policy as well as incorporation of selected characteristics of the raters. Further improvements in this domain will require a deeper understanding of the rating process. While our work strongly suggests that the UC SRAP cannot be reliably applied as written, the high levels of agreement in specific aspects of the policy indicate that some policy elements may be more problematic than others. For example, the high Rand indices would suggest that policy users agreed, on a per patient basis, about the need for ICU and the presence of catastrophic conditions. While the Rand index for whether an exemption criterion was present was relatively

high at 0.85, it was noticeably lower than the prior two determinations, suggesting that the reliable identification of exemption criteria might be an area for further focus. From our knowledge of the study, we suspect that some of this disagreement may have been driven by inappropriate extension of the exemption – for instance, a patient who was more than 10 days out from transplant surgery should not have been given an exemption but may have been assigned Violet because they had received a transplant.

Additionally, there was relatively high agreement in the determination of the presence or absence of the comorbidities by the Rand indices – only three comorbidities had a Rand index less than 0.9. These results support the addition of a calibration process that includes real-time feedback from raters to understand areas of ambiguity or confusion. Such calibration processes might include testing the removal of specific comorbidities and exemption criteria and assessing their impact on reliability. For instance, one might consider collapsing the heart failure Comorbidities M2 and S2 into a single condition, which would directly address the lower levels of agreement in Comorbidity M2, or removing these conditions from the policy entirely, given that they were not found to be associated with risk of mortality in the simulation studies.

Future research around resource allocation policies should take care to design studies that reflect the real-world issues that impact implementation of such policies. For example, while interrater reliability measures can be calculated from two raters each evaluating the same number of patients, such a design would prevent any evaluation of variation among raters, which is a foreseeable issue in enacting a policy such as the UC SRAP that intends to train multiple individuals of varying backgrounds and experiences who will bring those to the rating process in the form of potential biases. Awareness of this component of the IRR measure is critical in optimizing these policies for reliable implementation.

Optimizing Mortality Outcomes Related to Policy Implementation

Simulation methods like those leveraged here are a powerful tool in conducting an otherwise ethically difficult experiment. Given the abundance of ICU patient data collected across hospitals on a constant basis for the purposes of patient care, our healthcare system is fortunate to have arguably the most valid inputs into any microsimulation model aimed at assessing the impact of allocation policies that rely directly on individual patient data. As previously summarized literature and our model selection highlights, large datasets with heterogeneity at many levels (age, racial, ethnic, language, hospital, city, state, etc.) are ideal to fully exploit the power of microsimulation.

Finally, these simulation programs would be even more useful with the modifiable policy "built-in" such that criteria could be added and removed with immediate calculation of the impact on mortality outcomes. In the case of our dataset, the Triage Categories were given as input data, such that adding or removing a Policy Criteria variable would not have changed the allocation priorities or subsequent decisions. Incorporating the determination of the allocation decision variable into the simulation as based on other variables would offer an unmatched ability to further guide resource allocation policy development.

Mitigating the Impact of Existing Disparities

Larger datasets are needed to fully understand the impact of resource allocation policies on racial disparities. Although it cannot be definitively concluded given that almost one-third of our population's racial identity was unknown, it is unlikely that our sample was representative of the Los Angeles demographic, let alone California or the United States, based on the most recent census data available.[44,59,60]

Furthermore, given the relatively low prevalence of any single comorbidity in our sample, as shown in Table 21, it is unlikely that our analyses would be powered to detect mediation effects of race by a particular comorbidity. In the context of the UC SRAP and other policies that

give equal weight to any one diagnosis within a set, sensitivity analyses can still be conducted around the inclusion and exclusion of specific comorbidities and the resulting change to the impact of the Comorbidity Component on risk of mortality. For example, one might ask how removing Comorbidity S5 (cirrhosis with a MELD > 20), which was present in approximately 10 percent of our patient sample, from the list of severely life-limiting comorbidities would change the allocation decisions and expected cohort mortality.

Our work focused on disparities between racial groups driven by difference in SOFA scores and specific comorbidities like end-stage renal disease, cirrhosis, and cancer, but the microsimulation framework is agnostic to the choice of patient characteristic and can be applied to the study of other forms of disparities. Given the concerns raised about the role that socioeconomic status (SES) may play in the disproportionate burden of cancer in minorities, one might use our framework to explore how policy modifications such as the inclusion of the SVI could work to mitigate the impact of prior disparities on the resource allocation process. The SVI is a multi-domain indicator developed by the CDC to identify social vulnerable populations at risk of needing increased support during public health emergencies.[61] Such a data point, when linked to individual chart-level data, could provide insight into how incumbent societal disadvantages impact the severity of presenting critical illness and/or the presence of comorbid conditions, furthering our understanding of existing disparities and potentially offering a mechanism to mitigate these otherwise unmeasured disparities in resource allocation.

Future Directions

There remains great potential for these frameworks to impact the quality and quantity of research conducted around healthcare resource allocation. As with all studies, the weight of the conclusions will rely heavily on the quality of the available data, which will require institutional investment in maintain high-quality medical records and optimizing workflows for such data collection. The modified SEIR framework presented in Chapter 3 also suggests that fully

94

understanding the outcomes of policies like the UC SRAP will require consideration of the input data. The patients who present for hospitalization and evaluation for critical care had a particular risk of requiring ICU care, that was born of their risks of exposure and susceptibility. Again, leveraging measures such as the SVI may allow researchers to understand these risks to create policies that are both equitable and effective in maximizing the number of lives saved.

Appendices

Appendix A: Common Terms and Abbreviations

Term or Abbreviation	Definition
CareConnect	Electronic medical record for the University of California, Los Angeles Health System
Catastrophic condition	One of five conditions specified by the Scarce Resource Allocation Policy corresponding to the lowest priority Triage Category Blue (Table 2, Appendix B)
COPD	Chronic Obstructive Pulmonary Disease
CSC	Crisis Standards of Care
ECMO	Extracorporeal Membrane Oxygenation
EMR	Electronic medical record
Exemption criterion	One of five criteria specified by the Scarce Resource Allocation Policy corresponding to the highest priority Triage Category Violet (Table 5, Appendix B)
ICC	Intraclass correlation coefficient
ICU	Intensive Care Unit
ICU indication	One of five indications specified by the Scarce Resource Allocation Policy corresponding to the Triage Category Green (Table 1, Appendix B)
IPF	Idiopathic Pulmonary Fibrosis
IRR	Interrater reliability
MELD	Model for End-Stage Liver Disease
mSOFA	Modified Sequential Organ Failure Assessment
SOFA	Sequential Organ Failure Assessment
SRAP	Scarce Resource Allocation Policy
Surge Conditions	Time periods during which supply of critical care resources is surpassed by patient need or demand for such resources
SVI	Social Vulnerability Index
TAT	Triage Allocation Tool
UC	University of California
UCLA	University of California, Los Angeles
uSOFA	UCLA-modified Sequential Organ Failure Assessment
WHO	World Health Organization

Appendix B: Various measures of severity of acute illness

Sequential Organ Failure Assessment (SOFA) Scoring System

Organ System	0	1	2	3	4
Respiratory P_aO_2/F_iO_2 on arterial blood gas (or S_pO_2/F_iO_2 when ABG not available)	≥ 400 (≥ 512)	300 – 399 (357 – 511)	200 – 299 (214 – 356)	100 – 199 (89 – 213)	< 100 (< 89)
Coagulation Platelet count ($10^3/\mu L$)	≥ 150	100 – 149	50 – 99	20 – 49	< 20
Liver Bilirubin (mg/dL)	< 1.2	1.2 – 1.9	2.0 – 5.9	6.0 – 11.9	≥ 12
Cardiovascular Hypotension (vasopressor doses in mcg/kg/min)	None	MAP < 70 mmHg	Dopamine < 5	Dopamine 6 – 15 or Epinephrine < 0.1 or Norepinephrine < 0.1	Dopamine > 15 or Epinephrine ≥ 0.1 or Norepinephrine ≥ 0.1
Central Nervous System Glasgow Coma Scale (GCS) Score	15	13 – 14	10 – 12	6 – 9	< 6
Renal Creatinine (mg/dL) (or urine output (mL/24h))	< 1.2	1.2 – 1.9	2.0 – 3.4	3.5 – 4.9 (< 500)	> 5 (< 200)

Modified Sequential Organ Failure Assessment (mSOFA) Scoring System

Organ System	0	1	2	3	4
Respiratory S_pO_2/F_iO_2 on arterial blood gas	(> 400)	(316 – 400)	(236 – 315)	(151 – 235)	(≤ 150)
Liver	No scleral icterus or jaundice			Scleral icterus or jaundice	
Cardiovascular Hypotension (vasopressor doses in mcg/kg/min)	None	MAP < 70 mmHg	Dopamine < 5	Dopamine 6 – 15 or Epinephrine < 0.1 or Norepinephrine < 0.1	Dopamine > 15 or Epinephrine ≥ 0.1 or Norepinephrine ≥ 0.1
Central Nervous System Glasgow Coma Scale (GCS) Score	15	13 – 14	10 – 12	6 – 9	< 6
Renal Creatinine (mg/dL)	< 1.2	1.2 – 1.9	2.0 – 3.4	3.5 – 4.9	> 5

UCLA-modified Sequential Organ Failure Assessment (uSOFA) Scoring System

Organ System	0	1	2	3	4
Respiratory P_aO_2/F_iO_2 on arterial blood gas (or S_pO_2/F_iO_2 when ABG not available)	≥ 400 (≥ 512)	300 – 399 (357 – 511)	200 – 299 (214 – 356)	100 – 199 (89 – 213)	< 100 (< 89)
Coagulation Platelet count ($10^3/\mu L$)	≥ 150	100 – 149	50 – 99	20 – 49	< 20
Liver Bilirubin (mg/dL)	< 1.2	1.2 – 1.9	2.0 – 5.9	6.0 – 11.9	≥ 12
Cardiovascular Hypotension (vasopressor doses in mcg/kg/min)	None	MAP < 70 mmHg	Dopamine < 5	Dopamine 6 – 15 or Epinephrine < 0.1 or Norepinephrine < 0.1	Dopamine > 15 or Epinephrine $\geq$ 0.1 or Norepinephrine $\geq$ 0.1 or ECMO
Central Nervous System Glasgow Coma Scale (GCS) Score	15	13 – 14	10 – 12	6 – 9	< 6
Renal Creatinine (mg/dL) (or urine output (mL/24h))	< 1.2	1.2 – 1.9	2.0 – 3.4	3.5 – 4.9 (< 500)	> 5 (< 200)

Appendix C: Excerpted criteria tables from the Scarce Resource Allocation Policy

Table 1: Inclusion criteria for consideration of critical care

Patient has an acute medical condition that would potentially benefit from critical care	
Requires invasive mechanical ventilation	• Refractory hypoxemia (SpO2<90% on non-rebreather mask at flow of ≥15 LPM) • Respiratory acidosis with pH < 7.20 on arterial blood gas • Clinical evidence of respiratory failure • Inability to protect airway
Requires vasoactive support for hypotension or unstable rhythm	• Systolic blood pressure < 90 mmHg with clinical evidence of shock (end-organ failure) refractory to volume resuscitation • Unstable bradyarrhythmia refractory to electrolyte replacement • Unstable tachyarrhythmia requiring vasoactive drip or cardioversion • Requires mechanical circulatory support
Requires extracorporeal life support	• Above criteria, plus assessment of acceptability by ECMO team
Requires intensive neurologic monitoring or intervention	• Acute neurologic condition (e.g. intracranial/intraventricular hemorrhage, subarachnoid bleed with unsecured aneurysm, traumatic brain injury, or ischemic stroke with mass effect or acute hydrocephalus, severe CNS infection) with Glasgow Coma Scale < 13 • Status epilepticus refractory to initial antiepileptic therapy • Spinal cord injury at or above C5 with ASIA-A and B criteria[24]
Requires intensive interventions for trauma or major surgical condition	• Trauma causing significant instability or neurologic insult • Post-operative condition with significant instability or requiring close critical care observation • Post-operative from endovascular or thrombolytic management of high-risk (e.g., ST-elevation) myocardial infarction, stroke, or thromboembolic disease for first 24 hours post-event

Table 2: Catastrophic medical conditions with low likelihood of short-term survival present at presentation

Refractory cardiac arrest	• Any unwitnessed out of hospital cardiac arrest without ROSC prior to arrival • Any witnessed cardiac arrest with inability to obtain ROSC after 60 minutes from onset without a shockable rhythm present
Hypoxic-ischemic brain injury after cardiac arrest	• Coma (inability to respond to verbal commands) after ROSC from cardiac arrest with non-shockable rhythm without confounding drugs, toxins, or metabolic derangements
Severe burns	• American Burn Association expected mortality ≥90% (Table 17 in Appendix 8)
Severe trauma	• Trauma Injury Severity Score predicting ≥90% mortality (Table 15 in Appendix 8)
Severe neurological injury (rule out confounders to clinical assessment such as sedation, transient seizure, or treatable hydrocephalus)	• Supratentorial intracerebral hemorrhage with ICH Score $\geq$ 5 • Brainstem intracerebral hemorrhage with deep coma (GCS $\leq$ 5) • Aneurysmal subarachnoid hemorrhage with Hunt-Hess score of 5 (Table 16 in Appendix 8) • Traumatic brain injury with $\geq$ 90% predicted death or persistent vegetative state at 6 months on IMPACT score[25] • Ischemic stroke with NIH Stroke Scale score $\geq$ 22 and either not eligible for acute revascularization or > 24 hours after revascularization treatment

N.B.: ROSC=return of spontaneous circulation, ICH=intracerebral hemorrhage; GCS=Glasgow Coma Scale

Table 3: Medical comorbidities and chronic conditions that limit short-term survival.

Major comorbidities that are associated with increased risk of short-term mortality from critical illness	Severely life-limiting comorbidities associated with high mortality even in absence of critical illness (survival typically ≤ 1 year), and which are correlated with significantly increased risk of short-term mortality from critical illness
• Pre-existing neurological condition (dementia, stroke, other neurodegenerative disease) with baseline modified Rankin Score ≥ 4 • ACC/AHA Stage C heart failure, NYHA Class II-IV • Severe, inoperable multi-vessel coronary artery disease or valvular disease • WHO Class 3 pulmonary hypertension (symptomatic with minimal exertion, asymptomatic only at rest) • Moderately severe chronic lung disease (e.g., COPD, IPF) but not requiring chronic oxygen or ventilation • End stage renal disease on dialysis • Cirrhosis with MELD <20 and history of prior decompensation	• Minimally conscious or unresponsive wakeful state from prior neurological injury • ACC/AHA Stage D heart failure • WHO Class 4 pulmonary hypertension • Severe chronic lung disease with FEV_1 < 20% predicted, FVC < 35% predicted, or in absence of PFTs, chronic home O_2 at rest or mechanical ventilation • Cirrhosis with MELD score ≥20 • Metastatic cancer with expected survival ≤1 year despite treatment • Refractory hematologic malignancy (resistant or progressive despite conventional initial therapy) • Terminal illness with Clinical Frailty Scale Score ≥8

N.B.: In the absence of appropriate expertise (which can include triage officer, backup officer, primary team, or rapid consultation) to evaluate, the patient is NOT docked for major comorbidities. Points for the items included in this table may be added to a patient at any time if they are discovered after admission to the ICU and reprioritization may be done as necessary.

Table 4: Multi-principle strategy to allocate critical care resources during crisis

Principle	Specification	Allocation Point System			
		1	2	3	4
Current Overall Clinical Status	*Prognosis for acute survival (SOFA or MSOFA[26] score)*	SOFA score < 6 or MSOFA <6	SOFA score 6-9 or MSOFA 6-8	SOFA score 10-12 or MSOFA 9-11	SOFA score > 12 or MSOFA>11
Co-occuring conditions that moderate mortality	*Co-occurring conditions that influence acute survival*	…	Major comorbid condition(s)	…	Severely life-limiting condition(s)
Deductions see Table 5 below.					

100

Table 5: Special considerations for triage allocation: exemptions and point adjustments

Group	Initial Triage	First reevaluation	Second reevaluation	Reevaluations thereafter
Critical worker (see Appendix 3 for definition)	Exempt for 72 hours, then initial triage at that time as usual, start triage clock at time 0 and deduct 4 points	Deduct 4 allocation points	Deduct 2 allocation points	Deduct 2 allocation points
Pregnant person (If estimated gestational age ≥24 weeks; if intrauterine fetal demise or delivery, then triage as usual)	Triage as usual, deduct 4 points	Triage as usual, deduct 4 points	Triage as usual, deduct 4 points	Triage as usual, deduct 4 points
Pre-transplant, active organ offer	Exempt only during time offer being evaluated, start triage clock at time of pause	Triage as usual	Triage as usual	Triage as usual
Post-operative, complex non-transplant surgery	Exempt for 120 hours, then initial triage at that time as usual, start triage clock at time 0	Triage as usual	Triage as usual	Triage as usual
Post-operative, transplant surgery	Exempt for 240 hours, then initial triage at that time as usual, start triage clock at time 0	Triage as usual, treat as if severe life-limiting comorbidity is resolved regardless of graft function for 90 days	Triage as usual, treat as if severe life-limiting comorbidity is resolved regardless of graft function for 90 days	Triage as usual, treat as if severe life-limiting comorbidity is resolved regardless of graft function for 90 days

Table 6: Initially assigning patients to triage categories using multi-principle scoring

Triage Categories	Assessment of Mortality Risk/Organ Failure
Red Highest priority for critical care services, higher likelihood of survival. Use life-saving resources as available.	Allocation Score 1-3
Orange Intermediate priority for critical care services, intermediate likelihood of survival. Use life-saving resources as available.	Allocation Score 4-6
Yellow Lower priority for critical care services, higher risk of death. Use life-saving resources as available.	Allocation Score 7-8
Green Critical care not currently needed due to clinical stability. Use alternative forms of medical intervention or defer or discharge. Reassess as needed.	No significant organ failure AND/OR No requirement for life-saving interventions
Blue Lowest priority for critical care services due to extremely high risk of death. Use alternative forms of medical intervention and/or palliative care or discharge. Reassess as resources become available.	Acute catastrophic condition (Criteria from Table 2)
Violet Temporary exemption from triage allocation scoring. Continue to use critical care resources until exemption lapses.	See criteria in Table 5

102

Table 7: Multi-principle triage category first re-assessment (Hour 72)

Triage Categories	Assessment of Mortality Risk/Organ Failure
Red Highest priority for critical care services, higher likelihood of survival. Use life-saving resources as available.	Allocation Score 1-3
Orange Intermediate priority for critical care services, intermediate likelihood of survival. Use life-saving resources as available.	Allocation Score 4-6
Yellow Lower priority for critical care services, higher risk of death. Use life-saving resources as available.	Allocation Score 7-8 OR Increase in allocation score of $\geq$ 3 points from increase in SOFA from any initial score[1]
Green Critical care not currently needed due to clinical stability. Use alternative forms of medical intervention or defer or discharge. Reassess as needed.	No longer ventilator dependent or actively weaning from ventilator AND/OR No longer in need of circulatory support/drips
Blue Lowest priority for critical care services due to extremely high risk of death. Use alternative forms of medical intervention and/or palliative care or discharge. Reassess when resources become available.	Acute catastrophic condition (Table 2)*
Violet Temporary exemption from triage allocation scoring. Continue to use critical care resources until exemption lapses.	See criteria in Table 5
* If a patient develops a catastrophic condition (Table 2) before first reassessment, re-triage to blue	

Table 8: Multi-principle triage category re-assessment (Hour 144, then each 72h thereafter)

Triage Categories	Assessment of Mortality Risk/Organ Failure
Red Highest priority for critical care services, higher likelihood of survival. Use life-saving resources as available.	Allocation Score 1-3
Orange Intermediate priority for critical care services, intermediate likelihood of survival. Use life-saving resources as available.	Allocation Score 4-6
Yellow Lower priority for critical care services, higher risk of death. Use life-saving resources as available.	Allocation Score 7-8 OR Increase in allocation score ≥2 points from increase in SOFA since previous assessment[1]
Green Critical care not currently needed due to clinical stability. Use alternative forms of medical intervention or defer or discharge. Reassess as needed.	No longer ventilator dependent or actively weaning from ventilator AND/OR No longer in need of circulatory support/drips
Blue Lowest priority for critical care services due to extremely high risk of death. Use alternative forms of medical intervention and/or palliative care or discharge. Reassess when resources become available.	Acute catastrophic condition (Table 2)[*]
Violet Temporary exemption from triage allocation scoring. Continue to use critical care resources until exemption lapses.	See criteria in Table 5

[1] Despite low or moderate previous score, patient has worsened significantly
[2] If a patient develops a catastrophic condition (Table 2) before reassessment, re-triage to blue

Appendix D: Screenshots of the Triage Allocation Tool

Screenshot 1

Summary | Chart | Notes | Orders | Results | Synopsis | I/O | History | Triage Priority | Periop

Triage Priority

TRIAGE ALLOCATION
GCS
Triage Allocation

RESOURCES ALLOTTED
Resources Allotted

GCS

+ New Reading

Flowsheets

ED to Hosp-Admission (Current) from 1/4/2021 in RRUMC 8 Intensive Care Unit

	3/1/21 0800	1921	3/2/21 0800	2100	3/3/21 0800	2100	3/4/21 0000	0400	0800
Glasgow Coma Scale									
Eye Opening	Spontaneous	Spontaneous	Spontaneous	Spontaneous	Spontaneous	Spontaneous	Spontaneous	Spontaneous	Spontaneous
Best Verbal Response	Oriented	Oriented	Oriented	Oriented	Oriented	Confused	Confused	Confused	Oriented
Best Motor Response	Obeys commands	Obeys commands	Obeys commands	Obeys commands	Obeys commands	Obeys commands	Obeys commands	Obeys commands	Obeys commands
Glasgow Coma Scale Score	15	15	15	15	15	14	14	14	15

Triage Allocation Code

+ New Reading

Flowsheets

Triage Allocation Score

	View older data	ED to Hosp-Admission (Current) from 1/4/2021 in RRUMC 8 Intensive Care Unit 03/04/21 0000	ED to Hosp-Admission (Current) from 1/4/2021 in RRUMC 8 Intensive Care Unit 03/04/21 0400	ED to Hosp-Admission (Current) from 1/4/2021 in RRUMC 8 Intensive Care Unit 03/04/21 0801	ED to Hosp-Admission (Current) from 1/4/2021 in RRUMC 8 Intensive Care Unit 03/04/21 1201
uSOFA Score (Do Not Edit)		9	9	9	12

Resources Allotted

+ New Reading

Flowsheets

		ED to Hosp-Admission (Current) from 1/4/2021 in RRUMC 8 Intensive Care Unit 1/27/21 1418
Resources Allotted		
Has critical care been allocated?		Yes
Resources Allotted List		—
Resources Allotted Comment		—

Screenshot 2

Summary | Chart | Notes | Orders | Results | Synopsis | I/O | History | Triage Priority | Periop | Rounding

Triage Priority

TRIAGE ALLOCATION
GCS
Triage Allocation

RESOURCES ALLOTTED
Resources Allotted

Triage Allocation Code

Show: ☐ Row Info ☑ Last Filed ☐ Details

Time taken: 2016   1/26/2021   Values By

∨ Triage Allocation Score
∨ Triage Allocation

Stable Patient - No Higher Level Care Required   [Yes] [No]
No
by Emeruwa, Iheanacho O., MD
at 01/15/21 1548

Triage Allocation Code
RED (calculated)
by Emeruwa, Iheanacho O., MD
at 01/15/21 1548

◄◄ Restore   ✓ Close   ✗ Cancel   ↑ Previous   ↓ Next

Resources Allotted

+ New Reading

Flowsheets

No data found.

105

Triage Priority

TRIAGE ALLOCATION
GCS
Triage Allocation

RESOURCES ALLOTTED
Resources Allotted

Comorbidities	0=No 2=Yes (Table 1) 4=Yes (Table 2) Unknown/Unavailable
	0=No by Emeruwa, Iheanacho O., MD at 01/15/21 1548

Comorbidities Table1
- [ ] Pre-exist neuro condition, baseline mRankin > or equal to 4
- [ ] ACA/AHA Stage C, NYHA Class II-IV heart failure
- [ ] Severe/inoperable CAD or valve dz
- [ ] WHO Class 3 Pulm HTN
- [ ] Mod severe chronic lung dz, not on home O2
- [ ] ESRD on dialysis
- [ ] Decompensated cirrhosis MELD<20

Comorbidities Table2
- [ ] Min consciousness/unresponsive wakeful state from prior neuro injury
- [ ] ACA/AHA Stage D heart failure
- [ ] WHO Class 4 Pulm HTN
- [ ] Severe chronic lung dz, FEV1<20% predict or FEV< 35% predict w/home O2, or mech vent
- [ ] Cirrhosis MELD > or equal to 20
- [ ] CA w/mets or hem malignancy w/poor prognosis
- [ ] Terminal illness any cause w/frailty score > or equal to 8

HCW Deductions	0=No -4=HCW (Post 72Hrs Eval) -2=HCW (Post 72 Hrs Subsequent Eval) Unknown/Unavailable
	0=No by Emeruwa, Iheanacho O., MD at 01/15/21 1548
Pregnant >24 weeks	0=No -4=Yes Unknown/Unavailable
	0=No by Emeruwa, Iheanacho O., MD at 01/15/21 1548
Triage Allocation Score	
	2 (calculated) by Emeruwa, Iheanacho O., MD at 01/15/21 1548
Triage Allocation Code	CODE not Calculated
	CODE not Calculated (calculated) by Emeruwa, Iheanacho O., MD at 01/26/21 2016

Restore Close Cancel   Previous Next

Disaster/Pandemic Triage Team [10785403] as of Thu 3/4/2021 11:35 PM

Filters Options Hospital Chart Add to List

Select All

Room/Bed	MRN	Attending	Service	Triage Allocation Code	Triage Allocation Code (Last 2 Filed)	Resources Allotted?	Resources Allocated List	Time Since Las
4413-A			Medicine - Critical Care (ICU)	CODE not Calculated@2/9/2021 0807	2/9/2021 08:07 [CODE not Calculated] 1/27/2021 07:57 [ORANGE]	Yes@1/27/2021 0757	Bed;CRRT	23d 15h 28m
7149-A			Medicine - General Internal	CODE not Calculated@2/18/2021 1015	2/18/2021 10:15 [CODE not Calculated]			14d 13h 20m
8117-A			Medicine - General Internal	GREEN@1/28/2021 0825	1/28/2021 08:25 [GREEN]			35d 15h 10m
8411-A			Surgery - Liver Services	RED@2/18/2021 1017	2/18/2021 10:17 [RED]			14d 13h 18m
8457-A			Surgery - Liver Services	CODE not Calculated@1/26/2021 2113	1/26/2021 21:13 [CODE not Calculated] 1/26/2021 20:53 [CODE not Calculated]	Yes@1/27/2021 1418		37d 02h 22m

5 of 5 results loaded

Images of the instrument forms are included on the following pages.

Demographics

Study ID

_____

MRN

_____

Last Name

_____

First Name

_____

Date and Time of Assessment

_____

Filed by

_____

Sex

○ Female
○ Male
○ Other / decline
○ Missing

DOB

_____

Marital Status

○ Single
○ Married / Partnered / Significant Other
○ Widowed
○ Divorced / Separated
○ Other
○ Unknown
○ Missing

Ethnicity

○ Not Hispanic or Latino
○ Hispanic or Latino
○ Decline / not disclosed
○ Missing

Street Address

_____

City

_____

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State	○ Alabama (AL)
	○ Alaska (AK)
	○ Arizona (AZ)
	○ Arkansas (AR)
	○ California (CA)
	○ Colorado (CO)
	○ Connecticut (CT)
	○ Delaware (DE)
	○ District of Columbia (DC)
	○ Florida (FL)
	○ Georgia (GA)
	○ Hawaii (HI)
	○ Idaho (ID)
	○ Illinois (IL)
	○ Indiana (IN)
	○ Iowa (IA)
	○ Kansas (KS)
	○ Kentucky (KY)
	○ Louisiana (LA)
	○ Maine (ME)
	○ Maryland (MD)
	○ Massachusetts (MA)
	○ Michigan (MI)
	○ Minnesota (MN)
	○ Mississippi (MS)
	○ Missouri (MO)
	○ Montana (MT)
	○ Nebraska (NE)
	○ Nevada (NV)
	○ New Hampshire (NH)
	○ New Jersey (NJ)
	○ New Mexico (NM)
	○ New York (NY)
	○ North Carolina (NC)
	○ North Dakota (ND)
	○ Ohio (OH)
	○ Oklahoma (OK)
	○ Oregon (OR)
	○ Pennsylvania (PA)
	○ Rhode Island (RI)
	○ South Carolina (SC)
	○ South Dakota (SD)
	○ Tennessee (TN)
	○ Texas (TX)
	○ Utah (UT)
	○ Vermont (VT)
	○ Virginia (VA)
	○ Washington (WA)
	○ West Virginia (WV)
	○ Wisconsin (WI)
	○ Wyoming (WY)
	○ American Samoa (AS)
	○ Guam (GU)
	○ Northern Mariana Islands (MP)
	○ Puerto Rico (PR)
	○ Virgin Islands (VI)
	○ Armed Forces Africa (AE)
	○ Armed Forces Americas (AA)
	○ Armed Forces Canada (AE)
	○ Armed Forces Europe (AE)
	○ Armed Forces Middle East (AE)
	○ Armed Forces Pacific (AP)

ZIP Code

_____

Is patient experiencing homelessness?   ○ No
                                        ○ Yes
                                        ○ Unknown

Occupation

_____
(-999 if Missing)

Language   ○ English
           ○ Spanish
           ○ Chinese
           ○ Korean
           ○ Vietnamese
           ○ Tagalog / Filipino
           ○ Farsi
           ○ Arabic
           ○ Armenian
           ○ Russian
           ○ Other
           ○ Missing

Race   ○ White
       ○ Black or African American
       ○ American Indian or Alaska Native
       ○ Asian
       ○ Native Hawaiian or Other Pacific Islander
       ○ Mixed
       ○ Other
       ○ Decline / not disclosed
       ○ Missing

Insurance   ○ Medicare
            ○ Medicaid
            ○ Private
            ○ VA / Tricare
            ○ Other
            ○ Uninsured
            ○ Missing

Sexual orientation   ○ Lesbian or gay
                     ○ Straight
                     ○ Bisexual
                     ○ Queer
                     ○ Choose not to disclose
                     ○ Missing

Gender identity   ○ Female
                  ○ Male
                  ○ Trans female
                  ○ Trans male
                  ○ Non-binary / something else
                  ○ Decline / not disclosed
                  ○ Missing

Height (cm)

_____

Weight (kg)

_____

BMI

_____

Triage Tool Auditor

Filed by	_____
Time score filed	_____
Event type	◯ Initial triage ◯ Re-triage
GCS eye	◯ 1 None ◯ 2 To pain ◯ 3 To speech ◯ 4 Spontaneous ◯ Missing
GCS verbal	◯ T Intubated (if noted in comments) ◯ 1 No response ◯ 2 Incomprehensible ◯ 3 Inappropriate words ◯ 4 Confused ◯ 5 Oriented ◯ Missing
GCS motor	◯ 1 No response ◯ 2 Decerebrate ◯ 3 Decorticate ◯ 4 W/D pain ◯ 5 Localize pain ◯ 6 Follow command ◯ Missing
Critical care indication	☐ None ☐ Respiratory failure ☐ Cardiovascular failure ☐ ECLS ☐ Neuro failure ☐ Trauma or post-op
Catastrophic conditions	☐ N/A ☐ Unknown/unavailable ☐ Refractory cardiac arrest ☐ Severe burns ☐ Trauma (general) ☐ Trama (neuro) ☐ Neuro injury
Exemptions	☐ N/A ☐ Unknown/unavailable ☐ HCW (first 72h) ☐ Active transplant offer ☐ Post-op non-transplant ☐ Post-op transplant

Comorbidities

	Present	Absent	Could not determine
Pre-existing neuro w/ mRankin ≥4	○	○	○
ACC/AHA Stage C, NYHA II-IV CHF	○	○	○
Severe/inoperable CAD or valve dz	○	○	○
WHO Class 3 PHTN	○	○	○
Mod/sev chronic lung dz, not on home O2	○	○	○
ESRD on HD	○	○	○
Decompensated cirrhosis, MELD < 20	○	○	○
Persistent vegetative state	○	○	○
ACC/AHA Stage D CHF	○	○	○
WHO Class 4 PHTN	○	○	○
Severe chronic lung dz FEV1< 20, FVC < 35, O2, or vent	○	○	○
Cirrhosis, MELD ≥ 20	○	○	○
Cancer mets or heme malignancy poor prognosis	○	○	○
Terminal illness any cause w/ frailty score ≥ 8	○	○	○

Comorbidity points	○ No ○ Unknown/unavailable ○ 2=Yes (table 1) ○ 4=Yes (table 2) ○ Missing data
HCW Deductions	○ None ○ Unknown/unavailable ○ HCW 4 points (first 72h post exemption) ○ HCW 2 points (subsequent 72h post exemption) ○ Missing
Pregnancy deduction (≥24 weeks)	○ Not pregnant ○ Unknown/unavailable ○ Pregnant (4 point deduction) ○ Missing data

Please input the audit raw SOFA score data below.

Mean arterial pressure	_____ (-999 if Missing)
Oxygen support	○ None ○ Low-flow O2 ○ HFNC, PAP, or ventilator ○ ECMO ○ Missing

---

Liters flow

_____
(-999 if Missing)

FiO2

_____
(-999 if Missing)

Respiratory - SpO2 [from vitals flow sheet]

_____
(-999 if Missing)

ECMO/VAD

- ○ No ECMO
- ○ Veno-venous ECMO (V-V)
- ○ Veno-arterial ECMO (V-A)
- ○ Other ECMO (e.g. V-V-V, V-V-A)
- ○ VAD
- ○ Impella
- ○ IABP
- ○ Missing

Dopamine dose (mcg/kg/min)

_____
(0 if none)

Epinephrine dose (mcg/kg/min)

_____
(0 if none)

Norepinephrine dose (mcg/kg/min)

_____
(0 if none)

Sedation/Paralysis

- ☐ None
- ☐ Cisatracurium
- ☐ Dexmedetomidine
- ☐ Fentanyl
- ☐ Ketamine
- ☐ Midazolam
- ☐ Propofol
- ☐ Other opiate
- ☐ Other BZD
- ☐ Other paralytic
- ☐ Missing data

RASS

- ○ -5
- ○ -4
- ○ -3
- ○ -2
- ○ -1
- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ missing data

UOP last 24h (in mL, round to nearest whole #)

_____
(-999 if Missing)

Platelet count

_____
(-999 if Missing)

Serum creatinine

_____
(-999 if Missing)

Bilirubin (total)

_____
(-999 if Missing)

ABG PaO2 (round to nearest whole #)

_____
(-999 if missing. ABG only (no VBG))

Dialysis

○ None
○ iHD < 24h ago
○ iHD > 24h ago
○ CRRT
○ Missing

Time finished

_____

Notes on scoring difficulties

_____

Triage Team Scores

Filed by

_____

Time score filed

_____

Event type
- ○ Initial triage
- ○ Re-triage

GCS eye
- ○ 1 None
- ○ 2 To pain
- ○ 3 To speech
- ○ 4 Spontaneous
- ○ Missing

GCS verbal
- ○ T Intubated (if noted in comments)
- ○ 1 No response
- ○ 2 Incomprehensible
- ○ 3 Inappropriate words
- ○ 4 Confused
- ○ 5 Oriented
- ○ Missing

GCS motor
- ○ 1 No response
- ○ 2 Decerebrate
- ○ 3 Decorticate
- ○ 4 W/D pain
- ○ 5 Localize pain
- ○ 6 Follow command
- ○ Missing

Triage Support Team Member who filed score	○ Anderson Ida
	○ Antongiorgi Zarah
	○ Aysola Ravi
	○ Bavolek Rebecca
	○ Bierer Gregory
	○ Briggs-Malonson Medell
	○ Buhr Russell
	○ Chang Steven
	○ Channick Richard
	○ Czypinski Linda
	○ Dicker Rochelle
	○ Federman Myke
	○ Galuska Lee
	○ Gitlin Marcy
	○ Gudzenko Vadim
	○ Huard Leanna
	○ Juliard Catherine
	○ Kao Yuhan
	○ Kerbel Russell
	○ Kirkpatrick Theresa
	○ Lazarus Michael
	○ Lee Roger
	○ Lieto Codie
	○ Meltzer Joe
	○ Morocco Mark
	○ Neville Thanh
	○ Nsair Ali
	○ Ptaszny Magdalena
	○ Qadir Nida
	○ Rowe Laura
	○ Sachs Carolyn
	○ Savitsky Eric
	○ Shah Digish
	○ Sheehan Patricia
	○ Singh Sumit
	○ Srivastava Neeraj
	○ Susanto Irawan
	○ Tillou Areti
	○ Wang Tisha
	○ Wenger Neil
	○ Wheaton Natasha
	○ Wong Dana
	○ Other (fill below)

Which other person filed the score?

_____

Critical care indication	☐ None
	☐ Respiratory failure
	☐ Cardiovascular failure
	☐ ECLS
	☐ Neuro failure
	☐ Trauma or post-op

Catastrophic conditions	☐ N/A
	☐ Unknown/unavailable
	☐ Refractory cardiac arrest
	☐ Severe burns
	☐ Trauma (general)
	☐ Trama (neuro)
	☐ Neuro injury

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118

Exemptions	☐ N/A
	☐ Unknown/unavailable
	☐ HCW (first 72h)
	☐ Active transplant offer
	☐ Post-op non-transplant
	☐ Post-op transplant

Calculated uSOFA - Total Score	○ 0
	○ 1
	○ 2
	○ 3
	○ 4
	○ 5
	○ 6
	○ 7
	○ 8
	○ 9
	○ 10
	○ 11
	○ 12
	○ 13
	○ 14
	○ 15
	○ 16
	○ 17
	○ 18
	○ 19
	○ 20
	○ 21
	○ 22
	○ 23
	○ 24
	○ MISSING DATA

Calculated uSOFA score - Coag	○ 0
	○ 1
	○ 2
	○ 3
	○ 4
	○ MISSING DATA

Calculated uSOFA score - CNS	○ 0
	○ 1
	○ 2
	○ 3
	○ 4
	○ MISSING DATA

Calculated uSOFA score - Renal	○ 0
	○ 1
	○ 2
	○ 3
	○ 4
	○ MISSING DATA

Calculated uSOFA score - Cardio	○ 0
	○ 1
	○ 2
	○ 3
	○ 4
	○ MISSING DATA

Calculated uSOFA score - Liver	○ 0
	○ 1
	○ 2
	○ 3
	○ 4
	○ MISSING DATA

Calculated uSOFA score - Respiratory	○ 0
	○ 1
	○ 2
	○ 3
	○ 4
	○ MISSING DATA

uSOFA Score point allocation	○ 1 (less than 6)
	○ 2 (6-9)
	○ 3 (10-12)
	○ 4 (>12)
	○ Missing data

Comorbidities

	Present	Absent
Pre-existing neuro w/ mRankin ≥4	○	○
ACC/AHA Stage C, NYHA II-IV CHF	○	○
Severe/inoperable CAD or valve dz	○	○
WHO Class 3 PHTN	○	○
Mod/sev chronic lung dz, not on home O2	○	○
ESRD on HD	○	○
Decompensated cirrhosis, MELD < 20	○	○
Persistent vegetative state	○	○
ACC/AHA Stage D CHF	○	○
WHO Class 4 PHTN	○	○
Severe chronic lung dz FEV1< 20/FVC< 35 or O2/vent	○	○
Cirrhosis, MELD ≥ 20	○	○
Cancer mets or heme malignancy poor prognosis	○	○
Terminal illness any cause w/ frailty score ≥ 8	○	○

Comorbidity points	○ No
	○ Unknown/unavailable
	○ 2=Yes (table 1)
	○ 4=Yes (table 2)
	○ Missing data

HCW Deductions	○ None ○ Unknown/unavailable ○ HCW 4 points (first 72h post exemption) ○ HCW 2 points (subsequent 72h post exemption) ○ Missing
Pregnancy deduction (≥24 weeks)	○ Not pregnant ○ Unknown/unavailable ○ Pregnant (4 point deduction) ○ Missing data
Triage allocation score (calculated)	○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ Blank (Missing Data)
Triage Allocation Code	○ Red ○ Orange ○ Yellow ○ Green ○ Blue ○ Violet ○ CODE NOT CALCULATED
Did the triage support team request help from the implementation team for this filing?	○ Yes ○ No

Care characteristics

Timestamp

_____

Filed by

_____

Date of hospital admission

_____

SARS-CoV2 PCR Status

○ Negative
○ Positive

Transplant status

○ None
○ Listed
○ Transplanted

Transplant type

☐ BMT/HSCT
☐ Heart
☐ Kidney
☐ Liver
☐ Lung
☐ Pancreas
☐ Small bowel
(Select all that apply)

Code status at time of admission

○ Full code
○ DNAR/DNI
○ DNI without DNR (Modified Code)
○ DNR without DNI (Modified Code)
○ Comfort care
○ Missing

Date of ICU admission

_____

Select all support modalities patient required during
ICU admission

☐ None
☐ Vasopressors
☐ HFNC
☐ NIPPV
☐ Mech Vent
☐ ECMO (V-A)
☐ ECMO (V-V)
☐ MCS (Impella, IABP, VAD)
☐ iHD
☐ CRRT
☐ cEEG/deep electrodes
☐ EVD/invasive neuro monitor

Date of ICU discharge

_____

Date of hospital discharge

_____

Vital status	○ Alive and still admitted
	○ Died in hospital
	○ Discharged alive, died outside of hospital
	○ Discharged alive, status unknown
	○ Discharged alive, confirmed alive at time of filing
	○ Vital status unknown

| Date of death | |
| | _____ |

| Palliative care consulted | ○ Yes |
| | ○ No |

Code status at time of death or discharge	○ Full code
	○ DNAR/DNI
	○ DNI without DNR (Modified Code)
	○ DNR without DNI (Modified Code)
	○ Comfort care
	○ Missing

| Date of vital status follow up | |
| | _____ |

SVI

Timestamp	_____
Filed by	_____
Census tract	_____
SVI (California)	_____

Form complete
○ Yes
○ No

Appendix F: Medical Record Data Fields and Dictionary

Patient Demographics: This table holds demographic information for the patients in the cohort.

There is only one row per patient.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
AGE	Patient current age (as of data extraction date), or if patient is known deceased, age at death (if known)	
SEX	Patient sex	Values in CareConnect include: Male, Female, Other or Unknown
RACE	Patient race	Patient race records are converted into more general race classifications (e.g., Chinese is represented as Asian). A detailed summary can be provided upon request.
ETHNICITY	Patient ethnicity	List of possible values can be provided upon request
VITAL_STATUS	Vital status	Known Deceased; Not Known Deceased Please note: Vital status is not known deceased or deceased status in EHR. Only in-hospital death is recorded, for the most part. Blank values in Care Connect are reported as "Not Known Deceased." Vital status data in CareConnect is not currently linked to the California death registry or any other sources e.g., CDC death data
LANGUAGE	Patient's primary language	List of possible values can be provided upon request
MARITAL_STATUS	Patient marital status	List of possible values can be provided upon request
RELIGION	Patient religion	List of all possible values can be provided upon request
GENDER_IDENT	Gender Identity of the patient	
SEXUAL_ORIENT	Patient's Sexual Orientation	
EDUCATION	Neighborhood Education Level of the patient	
ADI_STATERANK	Neighborhood area of deprivation index (ADI) ranked scores at the state level	A raw score is the actual score a neighborhood receives based on the theoretical domains that the ADI measures. A decile groups the ADI scores into 10 equal sections., categorizing the individual block group/neighborhood, with those in the first percentile being the least disadvantaged, and those in the hundredth being the most. Deciles are created for each state individually.
ADI_NATRANK	Neighborhood area of deprivation index (ADI) ranked scores at the national level	Link to Area Deprivation Index website: https://www.neighborhoodatlas.medicine.wisc.edu/

Patient Identifiers: This table holds identifying information for the patients in the cohort. There

is only one row per patient.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
MRN	Patient medical record number (MRN)	MRNs should have 7 digits. Please note that depending on how you import the data, some MRNs that have a leading "0" may show as only having 6 digits. This is because the MRN is missing its leading "0". Please correct this and add the leading 0 back into the dataset and also add the leading 0 back if looking up the patients in CareConnect for chart review.
DOB	Patient date of birth (DOB)	Format: MM/DD/YYYY
ZIP_CODE	Patient postal address, zip code	May be 9-digit zip code
DEATH_DATE	Patient death date (if known)	Format: MM/DD/YYYY
FIRST_ENCOUNTER_DATE	Patient's first encounter date	Format: MM/DD/YYYY
LAST_ENCOUNTER_DATE	Patient's last encounter date	Format: MM/DD/YYYY
LONGITUDE	Patient Address X-axis Longitude	
LATITUDE	Patient Address Y-axis Latitude	
SVI_SOCIO_ECON	Percentile ranking for Socioeconomic theme according to the Social Vulnerability Index	Null values show -999. This variable corresponds to RPL_THEME1. The CDC has used the 2018 American Community Survey 5-year dataset for their calculations. For more information visit: https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2018.html (document also attached)
SVI_HCOMP_LANG	Percentile ranking for Household language theme according to the Social Vulnerability Index	
SVI_MINO_LANG	Percentile ranking for Minority status and language theme according to the Social Vulnerability Index	Null values show -999. This variable corresponds to RPL_THEME3. The CDC has used the 2018 American Community Survey 5-year dataset for their calculations. For more information visit: https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2018.html (document also attached)
SVI_HTYP_TRANS	Percentile ranking for Housing type and Transportation theme according to the Social Vulnerability Index	

Field Name	Description	Comment
FIPS	Concatenation of County FIPS, State FIPS & Tract	Concatenation of County, Tract, and block group codes
STCOFIPS	Concatenation of State & County codes	Code which uniquely identifies a County in the United States. It's made out of the concatenation of State & County codes
TRACT_FIPS	Concatenation of State, County and Tract FIPS codes	This code can be used to match records to other data sources from the Census or any other organization that use the FIPS code at the census tract level as a reference
OCCUPATION	Patient occupation	

Encounters: This table holds data for encounters for the patient cohort. There can be multiple rows per patient, but only one row per encounter.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
IP_ENC_ID	A de-identified, unique ID number for the encounter (assigned by IP for coding purposes)	Use this variable to link to variables from other tables with encounter information e.g., diagnoses, procedures, vital signs, etc.
INPATIENT_DATA_ID	The internal ID number of the record used to determine how inpatient data is stored for the encounter.	
EPIC_ENCOUNTER_TYPE	Encounter type as recorded in Epic	List of possible values can be provided upon request
ENCOUNTER_DATE	Encounter date	Format: MM/DD/YYYY
ENCOUNTER_AGE	Age at time of encounter	
ADMIT_DATE	Admit date and time	Format: MM/DD/YYYY HH24:MI
DISCHARGE_DATE	Discharge date and time	Format: MM/DD/YYYY HH24:MI
HOSP_DISCHARGE_DISPOSITION	Hospital discharge disposition	List of possible values can be provided upon request
IP_VISIT_TYPE	Visit type	Values include: ED, ED to IP, IP, Ambulatory visit, Non-Acute institutional stay, Other ambulatory visit, No information, Unknown, Other
LOCATION	Physical location of care	

Hospital Unit Transfers: This table holds within-hospital patient movement event data on admit, discharge, transfer time and location.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
IP_ENC_ID	A de-identified, unique ID number for the encounter (assigned by IP for coding purposes)	Use this variable to link to variables from other tables with encounter information e.g., diagnoses, procedures, vital signs, etc.

Field Name	Description	Comment
EVENT_TYPE	Event type	Admit; Admit/Discharge; Discharge; Transfer
EVENT_DATETIME_IN	Patient date and time in	Format: MM/DD/YYYY HH24:MI
LOCATION	UCLA Location	
DEPARTMENT_ID	Department ID number	
DEPARTMENT_NAME	Department name	

Encounter Diagnoses: This table holds encounter diagnoses data for the patients in the

cohort. There can be multiple rows per patient as well as multiple rows per encounter.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
IP_ENC_ID	A de-identified, unique ID number for the encounter (assigned by IP for coding purposes)	Use this variable to link to variables from other tables with encounter information e.g., diagnoses, procedures, vital signs, etc.
DIAGNOSIS_DATE	Diagnosis date	Format: MM/DD/YYYY
ICD_TYPE	ICD Type	9 = ICD-9; 10 = ICD-10; Please note ICD-9 codes are used prior to Oct 1, 2015, and ICD-10 codes are used after
ICD_CODE	ICD Code	
ICD_DESCRIPTION	ICD Diagnosis Code Description	
PRIMARY_DIAGNOSIS_FLAG	Primary or secondary diagnosis	P = Primary; S = Secondary; blank = no value
ADMISSION_DIAGNOSIS_FLAG	Admit diagnosis flag	1 = Yes; 0 = No
PRESENT_ON_ADMISSION	Diagnosis was present on admission	1 = Yes; 0 = No
HOSPITAL_FINAL_DIAGNOSIS	Final hospital discharge diagnosis	1 = Yes; 0 = No

Procedures: This table holds procedure information for the patients in the cohort. There can be

multiple rows per patient as well as multiple rows per encounter.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
IP_ENC_ID	A de-identified, unique ID number for the encounter (assigned by IP for coding purposes)	Use this variable to link to variables from other tables with encounter information e.g., diagnoses, procedures, vital signs, etc.
PROCEDURE_DATE	Procedure date and time	Format: MM/DD/YYYY HH24:MI
PROCEDURE_TYPE	Procedure type	9 = ICD9, 10 = ICD10, CPT, HCPCS; Please note ICD-9 codes are used prior to Oct 1, 2015, and ICD-10 codes are used after
PROCEDURE_CODE	Procedure code	
PROCEDURE_DESCRIPTION	Procedure description	

Problem Lists: This table holds problem list info for the patients in the cohort. There can be

multiple rows per patient.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
IP_PROBLEM_LIST_ID	A de-identified, unique ID number for the problem list (assigned by IP for coding purposes)	
ICD_TYPE	ICD Type	9 = ICD-9; 10 = ICD-10; Please note ICD-9 codes are used prior to Oct 1, 2015, and ICD-10 codes are used after
ICD_CODE	ICD Code	
ICD_DESCRIPTION	ICD Diagnosis Code Description	
PROBLEM_DESCRIPTION	Problem description	This variable is a PHI/free text field
PROBLEM_STATUS	Problem status	Values include: Active, Deleted, or Resolved

Flowsheet Vitals: This table holds flowsheet information for vital signs for the patients in the

cohort. There can be multiple rows per patient.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
INPATIENT_DATA_ID	The internal ID number of the record used to determine how inpatient data is stored for the encounter.	
VITAL_SIGN_ID	The Vital Sign Measure ID associated with the Vital Sign Type	
VITAL_SIGN_TYPE	Vital sign types	Per the data elements template, providing data only on the patients' height, bmi, and weight
VITAL_SIGN_VALUE	The measure result (number)	
VITAL_SIGN_TAKEN_TIME	The date and time the measure was taken	Format: MM/DD/YYYY HH24:MI

Labs: This table holds all laboratory result information for the patients in the cohort. There can

be multiple rows per patient as well as multiple rows per encounter.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
IP_ENC_ID	A de-identified, unique ID number for the encounter	Use this variable to link to variables from other tables with encounter information

Field Name	Description	Comment
	(assigned by IP for coding purposes)	e.g., diagnoses, procedures, vital signs, etc.
IP_ORDER_PROC_ID	A de-identified, unique ID number for the order (assigned by IP for coding purposes)	
COMPONENT_ID	Laboratory component ID number	
COMPONENT_NAME	Laboratory component name	
SPECIMEN_TAKEN_TIME	Specimen taken date and time	Format: MM/DD/YYYY HH24:MI
RESULT_TIME	Laboratory result date and time	Format: MM/DD/YYYY HH24:MI
RESULT	Laboratory test result	This variable is a PHI/free text field
REFERENCE_UNIT	Laboratory test result reference unit	

Medications: This table holds medication information for the patients in the cohort. There can be multiple rows per patient as well as multiple rows per encounter.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
IP_ENC_ID	A de-identified, unique ID number for the encounter (assigned by IP for coding purposes)	Use this variable to link to variables from other tables with encounter information e.g., diagnoses, procedures, vital signs, etc.
IP_ORDER_MED_ID	A de-identified, unique ID number for the medication order (assigned by IP for coding purposes)	
START_DATE	Medication start date	Format: MM/DD/YYYY HH24:MI
END_DATE	Medication end date	Format: MM/DD/YYYY HH24:MI
EPIC_MEDICATION_ID	Medication ID number in CareConnect	
EPIC_MEDICATION_NAME	Epic medication name	
MEDISPAN_GENERIC_NAME	Medispan generic name	
MEDISPAN_CLASS_NAME	Pharmaceutical class of medication	
MEDISPAN_SUBCLASS_NAME	Pharmaceutical subclass of medication	
SIG	Provider instructions to patient for taking the medication	
FREQUENCY	Frequency of medication dosage	

Social History: This table holds social history information for the patients in the cohort. We included all values for the requested fields and provide only the latest value.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
SMOKING_TOBACCO_USER	Smoking Tobacco user	Values in the dataset include: Current Every Day Smoker, Current Some

Field Name	Description	Comment
		Day Smoker, Former Smoker, Heavy Tobacco Smoker, Light Tobacco Smoker, Never Assessed, Never Smoker, Passive Smoke Exposure - Never Smoker, Smoker, Current Status Unknown, Unknown If Ever Smoked
SMOKING_START_DATE	Smoking start date	Format: MM/DD/YYYY
SMOKING_QUIT_DATE	Smoking quit date	Format: MM/DD/YYYY
ALCOHOL_USER	Alcohol user	Yes; No
ALCOHOL_OUNCES_PER_WEEK	Alcohol drinks per week (average)	
IV_DRUG_USER	IV drug user	Y = Yes; N = No
ILLICIT_DRUG_FREQUENCY	Illicit drug frequency	
ILLICIT_DRUG_COMMENTS	Illicit drug comments (free-text)	This variable is a PHI/free text field
CONTACT_DATE	Date of the encounter when this piece of information was recorded	Format: MM/DD/YYYY
SDH_EDUCATION_LEVEL	Social determinants of health (SDH) question; categorical responses corresponding to highest level of school attended	
SDH_FINANCIAL_RES_STRAIN	Social determinants of health (SDH) question about financial resource strain	
SDH_IPV_EMOTIONAL_ABUSE	Social determinants of health (SDH) question about emotional abuse from an intimate partner	
SDH_IPV_FEAR	Social determinants of health (SDH) question about fear of an intimate partner	
SDH_IPV_SEXUAL_ABUSE	Social determinants of health (SDH) question about sexual abuse from an intimate partner	
SDH_IPV_PHYSICAL	Social determinants of health (SDH) question about physical abuse from an intimate partner	
SDH_ALCOHOL_FREQ	Social determinants of health (SDH) question about frequency of drinking alcohol	
SDH_ALCOHOL_DRINKS_P_DAY	Social determinants of health (SDH) question about number of standard drinks consumed in a typical day	
SDH_ALCOHOL_BINGE	Social determinants of health (SDH) question about binge drinking	
SDH_LIVING_W_SPOUSE	Social determinants of health (SDH) question about whether or not the patient is currently living with spouse or partner	
SDH_DAILY_STRESS	Social determinants of health (SDH) question about daily stress	
SDH_PHONE_COMMUNICATION	Social determinants of health (SDH) question about how often the patient socializes with friends or family over the phone	

Field Name	Description	Comment
SDH_SOCIALIZE_FREQ	Social determinants of health (SDH) question about how often the patient socializes with friends or family in person	
SDH_CHURCH_ATTENDANCE	Social determinants of health (SDH) question about how often the patient attends religious services	
SDH_CLUB_MTG_ATTEND	Social determinants of health (SDH) question about how often the patient attends club or other organization meetings in a year	
SDH_CLUB_MEMBER	Social determinants of health (SDH) question about whether the patient is a member of any clubs or organizations	
SDH_PHYS_ACT_DAYS_P_WK	Social determinants of health (SDH) question about how many days a week the patient exercises	
SDH_PHYS_ACT_MIN_P_SESS	Social determinants of health (SDH) question about how minutes the patient exercises on days that they exercise	
SDH_FOOD_INSEC_SCARCE	Social determinants of health (SDH) question about whether or not the patient had run out of food and was not able to buy more	
SDH_FOOD_INSEC_WORRY	Social determinants of health (SDH) question about whether the patient worried about food running out in the past year or not	
SDH_MED_TRANS_NEEDS	Social determinants of health (SDH) question about whether the patient had difficulty regarding transportation for medical appointments and medicine	
SDH_OTHER_TRANS_NEEDS	Social determinants of health (SDH) question about whether the patient had difficulty regarding transportation for things other than medical appointments and medicine	

Flowsheets: This table holds flowsheet information for non-vital signs for the patients in the

cohort. There can be multiple rows per patient.

Field Name	Description	Comment
IP_PATIENT_ID	A de-identified, unique ID number for the individual patient (assigned by IP for coding purposes)	Use this variable to link to variables from all other files that contain patient information
INPATIENT_DATA_ID	The internal ID number of the record used to determine how	

Field Name	Description	Comment
	inpatient data is stored for the encounter.	
TEMPLATE_NAME	Template Name of the flowsheet measure	
DISPLAY_NAME	Display Name of the flowsheet measure	
MEASURE_NAME	Measure Name of the flowsheet measure	
FLOWSHEET_MEASURE_ID	The Flowsheet Measure ID associated with the Flowsheet Measure Type	
FLOWSHEET_MEASURE_TYPE	Flowsheet measure types	
FLOWSHEET_MEASURE_VALUE	The measure result	
FLOWSHEET_MEASURE_TAKEN_TIME	The date and time the measure was taken	Format: MM/DD/YYYY HH24:MI

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