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Causal Effects and Optimal Policy Learning for Intensive Care Unit Discharge Decisions to Solve Hospital Process Bottlenecks: Approach, Methods, and First Results

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Causal Effects and Optimal Policy Learning for Intensive Care Unit Discharge Decisions to Solve Hospital Process Bottlenecks: Approach, Methods, and First Results

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Declarations

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None.

Author contributions

JV: Conceptualization, Methodology, Formal analysis, Interpretation, Writing – Original Draft, Visualization, Supervision, Project administration, Final approval, Funding acquisition

JC: Conceptualization, Methodology, Data curation, Formal analysis, Interpretation, Writing – Review & Editing, Final approval

MF: Conceptualization, Data acquisition, Interpretation, Writing – Review & Editing, Final approval

Ethics approval and consent to participate

This study was approved by the Ethical Commission of Eastern Switzerland (project number 2024-00829).

Consent for publication

Not applicable.

Data availability

Anonymized personal health data with restricted access.

Code availability

Available from the corresponding author upon request.

Abstract

Intensive care units (ICUs) operate with fixed capacities and face uncertainty such as demand variability, leading to demand-driven, early discharges to free up beds. These discharges can increase readmission rates, negatively impacting patient outcomes and aggravating ICU bottleneck congestion. This study investigates how ICU discharge timing affects readmission risk, with the goal of developing policies that minimize ICU readmissions, managing demand variability and bed capacity.

To define a binary treatment, we randomly assign hypothetical discharge days to patients, comparing these with actual discharge days to form intervention and control groups. We apply two causal machine learning techniques (generalized random forest, modified causal forest). Assuming unconfoundedness, we leverage observed patient data as sufficient covariates. For scenarios where unconfoundedness might fail, we discuss an IV approach with different instruments.

We further develop decision policies based on individualized average treatment effects (IATEs) to minimize individual patients' readmission risk. We find that for 72% of our sample (roughly 12,000 cases), admission at point in time t as compared to $t + 1$ increases their readmission risk. Vice versa, 28% of cases profit from an earlier discharge in terms of readmission risk. To develop decision policies, we rank patients according to their IATE, and compare IATE rankings for instances, when demand exceeds the available capacity.

Finally, we outline how we will assess the potential reduction in readmissions and saved bed capacities under optimal policies in a simulation, offering actionable insights for ICU management. We aim to provide a novel approach and blueprint for similar operations research and management science applications in data-rich environments.

1 Introduction

The intensive care unit (ICU) of a hospital treats critically ill patients often suffering from life-threatening diseases (Gopalan and Pershad, 2019; Milbrandt et al., 2008; Nates et al., 2016). An ICU is characterized by scarce, costly capacities such as high-end hospital beds and medical equipment, and specialized physicians and nurses. These capacities are fixed in the short- to mid-term. In addition, patient demand and the patients' complexity mix are uncertain (Dobson et al., 2010; Thirumalai et al., 2024). Patients arrive due to scheduled surgeries, e.g., for post-surgery observation, or as external or internal emergencies. Prediction of the volume of incoming patients is difficult, and rarely done in practice. Additionally, patients' length of stay in the ICU is also uncertain as it depends, among other factors, on patients' main diagnosis, co-morbidities, performed procedures, and the progression of patients' health status. Lastly, process times of prior process steps, i.e., emergency care or surgery, are much smaller (hours) than patients' length of stay in the ICU (days). Fixed capacities, uncertain and unscheduled incoming demand, uncertain process times, and faster throughput time of upstream processes make the ICU into a classic example of a process bottleneck (Bai et al., 2021; Chan et al., 2012). Unlike classic production settings, inventory cannot be built between process steps and areas, however: Arriving patients are in great need for care and thus need intensive care immediately. If the ICU's capacity is fully utilized, one option is to discharge a patient with a relatively low need for intensive care (Berk and Moinezhadeh, 1998; Dobson et al., 2010). Discharging a patient in such a setting is referred to as demand-driven or early discharge, that is, if there were no newly arriving patient, the patient to be discharged would stay longer in the ICU, profiting from additional intensive care (Bai et al., 2021, 2018; Chan et al., 2012; Ouyang et al., 2020).

Demand-driven discharges, in turn, are linked to higher ICU readmission rates (Kramer et al., 2013, 2012; Niven et al., 2014). Indeed, the health status of patients discharged in demand-driven settings are more likely to worsen downstream, requiring a readmission to and additional stay in the ICU. Such readmissions not only gravely negatively impact patients' health and outcomes (Mcneill and Khairat, 2020; Rosa et al., 2020) and hospitals' bottom line, but they also additionally clog the ICU process

bottleneck – and might trigger additional demand-driven discharges, potentially setting off a vicious cycle (KC and Terwiesch, 2011).

We define an ICU discharge on a given day as the variable of interest (“treatment” in the econometric sense), causally linked to an outcome (i.e., ICU readmission). We formulate how a patient’s discharge on a given day causally effects a patient’s risk of readmission. Our goal is to discover a decision policy that minimizes ICU readmissions causally linked to (early) ICU discharge. To this goal, we plan to show that in situations where there is more than one candidate that could be discharged to accommodate a newly arriving patient, readmission risk is minimized by discharging the patient for whom the effect of discharge on readmission risk is smallest.

The gold standard for causal inference is a randomized experiment or a randomized controlled trial. Such a study design is very difficult or rather impossible to implement – both from an ethical as well as operational point of view – for our research endeavor. Thus, we present an approach that uses observational data and causal inference under the selection on observables assumption, also referred to as unconfoundedness or conditional independence assumption. Our research questions for developing an empirical approach and methodology are:

- I How can the causal effect of an ICU discharge on a given day on the ICU readmission risk of a patient be estimated with observational data?
- II How can a decision policy be learned that minimizes ICU readmissions?

Research questions I and II structure our research objective in two concrete steps: First, estimating the causal effect and second, learning a decision policy based on the estimated causal relationship, exploiting effect heterogeneity. Note that both steps need to consider individual patient characteristics to enable decision makers to make a discharge decision in a setting of uncertainty.

There is a rich operations management (OM) and medical literature on ICU management (Bai et al., 2018; Gopalan and Pershad, 2019; Niven et al., 2014), some of which we will review in the next chapter. As for many operations research settings (Ho et al., 2017), OM models address the ICU process bottleneck problem with normative mathematical models, aiming to develop decision policies from a

theoretical framework. Commonly, studies then test and/ or calibrate their models with (small) samples from one or several hospitals (e.g., Bai et al., 2021; Chan et al., 2012), or perform a simulation study (Ouyang et al., 2020).

In this paper, we outline that due to the causal relationship of ICU discharge and ICU readmission and individual patient characteristics creating variation and uncertainty, a different approach might be more effective, generalizable, and better scalable than traditional OM methods. While we also develop our model from a theoretical start point, its main strength comes from its empirical application and practicality. We aim to show that machine learning methods from the family of doubly robust learners can answer our research questions yielding data-driven decisions that optimize medical quality and free up scarce capacity. We believe that our approach is not only valid for ICU management and other hospital operations settings but that our study can serve as a blueprint for a more general application of causal machine learning methods in operations research.

This section continues with a review of related work. Section 2 presents a formal problem statement. Section 3 discusses our approach for estimating causal effects and developing optimal decision policies. We also present first descriptive results, and first estimations of causal effects. Lastly, we outline a simulation study to assess the practical utility of our approach. Section 4 summarizes and gives an outlook.

Related work

We apply machine learning methods for causal inference and policy learning to a hospital operations problem, more specifically for resolving one reason for bottleneck congestion of a key hospital process area, the ICU. Thus, related work of our study are studies in the OM literature focusing on (1) machine learning applications, (2) causal inference and causal machine learning, (3) policy learning, and (4) hospital operations.

Machine Learning Applications

Regarding machine learning applications, many studies focus on prediction in supervised learning settings. Chou et al. (2023) provided a review of studies published in leading OM journals applying a

variety of prediction algorithms such as random forest, gradient boosting, logistic or probit regression, or support vector machine. The authors note that the aim of the majority of studies is to show that machine learning prediction techniques work better than other (statistical) methods commonly applied or are more precise than status quo decision making (i.e., managerial judgement). In the healthcare context, Ang et al. (2015) employ a Q-Lasso technique to anticipate waiting times of low-acuity patients in emergency departments of four different hospitals. They show that their method is superior for the prediction and management of waiting times compared to rolling average approaches, “state-of-the-art” in practical emergency department management at the time of the study. Mukhopadhyay et al. (2021) compare the performance of six machine learning classifiers (e.g., neural networks, decision trees, and naïve-Bayes) with a linear programming model they built to detect diseases in four different datasets (two for breast cancer, one for diabetes, and one for diabetic retinopathy). Nenova and Shang (2022) develop an intelligent case-based reasoning approach to predict disease progression for patients suffering from chronic kidney disease and compare results to different machine learning and statistical models. The authors find that their approach outperforms other models. Lastly, Ko et al. (2019) employ machine learning methods to generate insights from textual patient reviews and use these insights to investigate the relationship between waiting time and patient satisfaction.

Causal Inference and Causal Machine Learning

In the last decade, an increasing number of studies employing methods for causal inference under the selection of observables assumption have been published in leading OM journals (Ho et al., 2017; Yilmaz et al., 2024). These studies evaluate effects of, for instance, introducing a new scheduling policy or production program, commonly using regression discontinuity designs or pre-post intervention study designs such as difference-in-differences or synthetic control methods. While we also aim to causally infer effects of a treatment (i.e., ICU discharge at a given point in time) on an outcome (i.e., change of a patient’s readmission risk) under the selection on observables assumption, our setting differs to traditional policy or program evaluation settings: We do not know the decision policy for selecting a patient for discharge yet but develop a decision policy minimizing overall readmission risk causally

linked to discharges. To this end, we need to estimate conditional average treatment effects (CATEs), more specifically the effect of a discharge at point in time t for a patient group (group average treatment effect, GATE), and at the most detailed aggregation level of patient features (individualized average treatment effect (IATE)) (Lechner and Mareckova, 2024). In the last years, causal forests were refined to estimate heterogenous treatment effects (HTE), which can be used for GATE and IATE estimation (Athey et al., 2019; Athey and Imbens, 2016; Chernozhukov et al., 2018; Feuerriegel et al., 2024; Lechner and Mareckova, 2024; Wager and Athey, 2018; Wang et al., 2021). Causal forests are suitable for our research setting which we outline in more detail in section 3.

Causal machine learning methods for the estimation of heterogenous treatment effects have, to the best of our knowledge, only been applied to very few operation research issues. Cui and Davis (2022) employ causal forest (Athey et al., 2019; Wager and Athey, 2018) combined with a difference-in-differences framework to estimate heterogenous treatment effects of occupancy taxes for Airbnb bookings on Airbnb listings. Wang et al. (2021) expanded on advances in the machine learning literature, adding an instrumental variable forest (IVF) approach to address endogeneity issues in observational data. The authors apply this approach in another study (Wang et al., 2023) to investigate the heterogeneity of outcome differences between hospitals, to compare the quality ranking of hospitals according to patient-centric versus population-average information, and to simulate implications for pay-for-performance reimbursement schemes. In their first study, Wang et al. (2021) show with experiments, that in settings of endogeneity, their IVF approach is superior to a causal forest approach without instrumental variable to correct for biases. They also show that IVF outperforms causal forests with instrumental variable as part of the generalized random forests (GRF) (Athey et al., 2019), especially when the instrumental variable is continuous. The authors conclude that IVF should be used when unconfoundedness cannot be argued and only continuous instrumental variables are available. Endogeneity issues and potential strategies to offset endogeneity such as instrumental variables are well-known and discussed in the OM literature (Lu et al., 2018). While we argue for unconfoundedness, in a variant of our model, we will also employ an instrumental variable approach (see section 3).

Policy Learning

Recently, methodologies and applications for policy learning have received increasing attention in the OM literature. Policy learning generally means employing machine learning methods to optimally assign treatment decisions, such as whom to offer a discount or whom to target with a certain drug, based on individuals' characteristics (Zhan et al., 2024). Athey and Wager (2021) developed the policy tree approach, a double robust machine learning technique for policy learning, which has been applied, discussed, and refined by several authors. Zhan et al. (2024), for instance, study how to extend policy learning when employing adaptively collected data, focusing on the two key challenges of (1) dependent samples in ex post optimal policy learning with adaptive samples, and (2) low assignment rates of different types of treatment to different types of individuals when using adaptive assignment rules. Munro (2024) explores how, under personalization of treatment assignment, strategic behavior of individuals trying to increase their chances to obtain a (better) treatment, might prevent optimal assignment. The author conducts a sequential experiment with Bayesian optimization to showcase a solution for managing individuals' strategic behavior.

Regarding applications, in their working paper, Cordier et al. (2023) combine causal forest with policy tree to learn what patients to optimally select for rapid recovery, a specific post-surgery treatment path for joint replacement patients, under capacity constraints. The authors show that optimal assignment rules can increase overall patient welfare, measured by patients' expected improvement of joint functionality, by 17.56% without increasing hospital capacity. Based on their insights, the authors derive implications for surgery scheduling and clinical decision support. Yang et al. (2023) impute long-term outcomes, namely long-term revenue from online subscribers of *The Boston Globe*, as input to learn an optimal policy for whom to target with discounts. The authors show that their imputation and policy learning strategy is comparable to a policy learned from ground-truth long-term outcomes and superior to status quo policy learning using short-term proxies for long-term outcomes.

Hospital Operations

Healthcare has become one of the core fields in operations research (Browning, 2020; Green, 2012). One important part of this research field is hospital operations management (Keskinocak and Savva, 2019).

Shi et al. (2021), for instance, design a Markov decision process to provide decision support for how many and what patients to discharge from a hospital on a given day, balancing readmission risk and inpatient congestion. They base these decisions on a personalized readmission prediction model, incorporating several statistical methods. Demir (2014) uses classification trees for predicting unplanned readmissions within 45 days after discharge for patients suffering from chronic obstructive pulmonary disease or asthma, and compares prediction results to other methods (e.g., logistic regression). Lastly, in their study, Berk and Moinzadeh (1998) find early discharges to be a viable option for increasing scarce capacities.

Within hospital operations management, many studies investigate ICU management (Bai et al., 2018). Chan et al. (2012) design an elaborate state and action space and dynamic optimization model to minimize the number of additional ICU inpatient days attributable to ICU readmissions linked to demand-driven discharges. Grand-Clément et al. (2023) design a Markov decision process model that uses predictions of patient deterioration supplied by machine learning models, to decide what patients should pro-actively be resubmitted to the ICU to prevent further patient deterioration, a longer length of stay, and deaths. They develop robust decision policies for transferring patients to the ICU, while stressing the effect of parameter uncertainty on average ICU occupancy, patients' length of stay, and mortality.

To reduce ICU process bottleneck congestion, apart from early discharges, hospitals could reject external or internal emergencies, and/ or cancel or reschedule elective surgeries in the case of surgical ICUs. Chan et al. (2012) consider these options in an extension to their model, and Bai et al. (2021) model a (stationary) discrete time Markov decision process considering these options and early discharge of a low- or high-severity patient as possible actions. While patient rejection can potentially alleviate bottleneck development (Scheulen et al., 2001), studies indicate several drawbacks (Chalfin et al., 2007; McConnell et al., 2005; Renaud et al., 2009; Schull et al., 2004). For instance, rejecting patients means lost revenue for a hospital, potentially negative impact on patient satisfaction when cancelling or rescheduling elective surgeries, and worse patient outcomes for rejected or diverted patients.

Besides, Ouyang et al. (2020) develop a mathematical model to support bed allocation decisions in the ICU. They develop policies for minimizing the long-run average mortality rate, and propose heuristic decision methods with relaxed, more general assumptions. They show the effectiveness of their heuristic methods in a simulation study. Lastly, they extend their model to deliberately allow for queuing for ICU admission and for readmission from the general ward.

Other work in the field of hospital operations management include an investigation of bottleneck and congestion spillover of one hospital unit to other units (Kim et al., 2023), the effect of advanced electronic medical records on patient safety (Hydari et al., 2018), optimal and predictive bed assignment (Bertsimas and Pauphilet, 2023), development of ICU admission policies by estimating the effect of denying admission on different patient outcomes (Kim et al., 2014), prediction of congestion risk in the ICU (Bravo et al., 2024), reduction of alarm fatigue (Piri et al., 2022), and understanding and better serving the needs of patients not critical enough to be treated in the ICU but too critical to be treated on a general ward (Chan et al., 2018).

There are also several studies in the medical literature investigating ICU discharge and readmission decisions. There are, for instance, reviews regarding ICU decision making (Gopalan and Pershad, 2019), studies informing guideline development (Nates et al., 2016), qualitative studies exploring the experience of physicians and nurses involved in and/ or affected by these decisions (Ofoma et al., 2018), and machine learning models predicting ICU readmission (Hammer et al., 2020; Loreto et al., 2020), which has also been studied by data scientists (Barbieri et al., 2020).

With our approach and methods, we do not only add to the operations research literature, but also to the literature on precision medicine, clinical decision support and optimal treatment selection (Feuerriegel et al., 2024; Prosperi et al., 2020). Finally, we refer to Prosperi et al. (2020) who correctly point out that machine learning models used for prediction do not deliver causal treatment suggestions, which is the main reason we are employing causal machine learning methods for causal inference rather than binary classifiers.

2 Formal Problem Statement

Conventional Models

Past OM studies have proposed Markov decision processes described by state and action space models to derive decision policies optimizing costs associated with demand-driven discharges and, by model extension (Chan et al., 2012) or as part of the main model (Bai et al., 2021), also rejection of arriving patients. They define the time period t with $t = \{1, 2, \dots, T\}$ to be small enough so only one patient can arrive in t . The arrival of a patient might require an action (e.g., demand-driven discharge), first and foremost in situations where the ICU bed capacity B is exceeded. Such an action, among other things such as changes of other patients' health status and "natural" discharges (service completion), changes the current state and defines the next state. The optimal policy, e.g., rejecting a patient, or early discharging one type rather than another type of patient, is then derived by minimizing the costs associated with the action associated with the policy (e.g., the additional ICU inpatient days "caused" by readmissions due to ICU discharge). While the authors show how such models can improve ICU management, we have three points of critique that impede transferability, scalability, and generalizability of existing models:

- 1) Causality: Costs or rewards of actions, i.e., the outcomes, are not causally linked to the policy, i.e., the treatment, in the econometric sense. Identifying assumptions, such as unconfoundedness or exogeneity, are not discussed and argued. Thus, it is unclear whether a change in costs is attributed to a policy (e.g., discharge patient x_1 rather than patient x_2 at point t) or to confounders.
- 2) Fixed and normative inputs: Costs or rewards are calculated with fixed inputs, e.g., the average length of stay of patients in the ICU, or normatively set money values. This reduces variation which empirically exists and could in fact be observed in the costs or rewards of actions. Such simplifications increase in sample performance but limit generalizability and scalability.
- 3) Bias and uncertainty of transition probabilities: Markov decision processes require identifying probabilities for transitioning from one state to another. In dynamic and complex settings, such probabilities have to be identified for many parameters (Bertsekas, 2012). A single biased

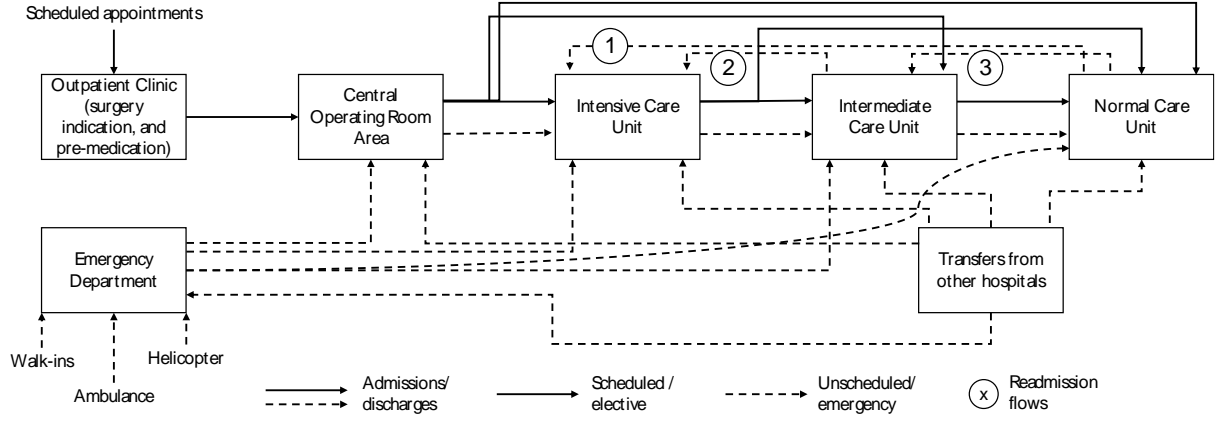
transition probability will bias the whole model. Additionally, the uncertainty of a point estimate of transition probabilities is usually not considered in Markov decision process models (Zhang et al., 2019). In other words, Markov decision process models implicitly assume point estimates from empiric data or expert estimates to be true probabilities. Indeed, uncertain transition probabilities have received attention in the literature for decades (e.g., Satia and Lave, 1973), and there are several approaches to address this issue (Delgado et al., 2011; Mastin and Jaillet, 2012; Zhang et al., 2019).

Practical ICU decision making: A novel problem statement

We propose a novel approach for addressing the limitations presented above. Firstly, we define a model based on practical ICU decision making which needs to resolve the bed capacity constraint $B_a \geq 0$ over the course of each day. Secondly, to help decision makers solve this constraint, we design policies that are generalizable, learnable with causal machine learning methods and re-learnable with the same algorithms and similar data from other hospitals, and thus scalable. Note also that state and action space models were shown to improve ICU decision making on a tactical level, e.g., when deciding whether and how much ICU capacity should be reserved to avoid more costly rejection and/ or early discharge (Bai et al., 2021). With our model, we will provide decision support for operational decision making in the ICU, i.e., for decisions that must be made routinely and daily.

We use the flow of a patient through a hospital as the starting point of our problem statement (cf. Figure 1, loosely based on Bai et al. (2021, 2018) and Litvak et al. (2008)). We are interested in reducing readmission flows (1), and (2). Kramer et al. (2013), for instance, report that the median readmission rate at more than 100 ICUs they investigated was at 5.9% (interquartile range 5.1% to 7.0%) and Hosein et al. (2014) found in a meta-analysis that readmission rates typically are between 4% and 6%. While a certain percentage of ICU readmissions appears to be nonpreventable (Al-Jaghbeer et al., 2016), preventable readmissions and especially those causally linked to discharges could be termed as rework and correction in Lean Management terms, adding to bottleneck congestion.

Figure 1: Hospital patient flow



Annotations: Patients can enter a hospital as scheduled, plannable cases (full arrows) through the outpatient clinic or as unscheduled/ emergency cases through the emergency department (dashed arrows). From the emergency department, patients are pushed onto the process area with free capacity and/ or where they need to receive care. Unscheduled transfers from other hospitals disrupt hospital system management further. Patients are pushed through the different process areas in a scheduled or oftentimes unscheduled manner. Demand planning and corresponding supply planning only regularly occur in the central operating room area, other process areas are commonly staffed corresponding to their full capacity (e.g., to serve all beds on a ward). We are particularly interested in how to minimize readmission flows (1) and (2), often causally linked to early, demand-driven discharges of patients in the ICU. In such situations, patients with the smallest risk of being readmitted due to the early discharge should be discharged, and not necessarily those with the lowest predicted readmission risk (cf. Athey (2017), and Prosperi et al. (2020) for a discussion of this topic).

The basis for our formal problem statement is the capacity constraint $B_a \geq 0$, denoting that the available ICU bed capacity B_a must always be equal to or greater than zero operatable ICU beds throughout a given day. In a naïve state, B_a is solely defined by the overall ICU bed capacity on a given day, and the sum of patients who will not be discharged and thus occupy the ICU $\sum_{i=1}^I x_i$ with $i = \{1, 2, \dots, I\}$ and $x = 1$ if x_i resides in the ICU at least for one more day, $x = 0$ otherwise:

$$B_a = B - \sum_{i=1}^I x_i \quad (1)$$

Consulting Figure 1, the first patient flow ICU decision-makers must consider and incorporate into (1) is the sum of elective surgery patients with a planned post-surgery ICU stay $\sum_{e=1}^E a_e$ on a given day, with $e = \{1, 2, \dots, E\}$, and $a = 1$ if a_e has a planned post-surgery ICU stay, $a = 0$ otherwise. In addition, planned discharges occur because a patient has reached ICU service completion (natural discharge), denoted by d_n with $n = \{1, 2, \dots, N\}$, and $d = 1$ if d_n is naturally discharged during the day, $d = 0$ otherwise. This expands the capacity constraints given in (1) into:

$$B_a = B - \left(\sum_{i=1}^I x_i + \sum_{e=1}^E a_e \right) + \sum_{n=1}^N d_n \quad (2)$$

If overall ICU capacity and natural discharges were sufficient to accommodate $\sum_{i=1}^I x_i$ and new arrivals $\sum_{e=1}^E a_e$, and if we stayed in this simplified decision framework, we could be satisfied with the definition of available ICU capacity as outlined in (2).

However, even if there were no unscheduled, external emergency patient arrivals, there are three additional considerations to make (cf. Figure 1). Given the capacity constraint $B_a \geq 0$, there will be days where $\sum_{e=1}^E a_e$ will require discharges in addition to $\sum_{n=1}^N d_n$, which we define as planned early, demand-driven discharges denoted by d_p^{early} with $p = \{1, 2, \dots, P\}$ and $d = 1$ if d_p^{early} is planned to be early discharged, $d = 0$ otherwise. Secondly, another lever to satisfy $B_a \geq 0$ is to reject patients, i.e. to cancel or postpone elective surgeries with a planned post-surgery ICU stay, denoted by $a_c^{elective}$ with $c = \{1, 2, \dots, C\}$, and $a = 1$ if $a_c^{elective}$ is cancelled, $a = 0$ otherwise. Thirdly, the capacity constraint must also hold when considering readmissions from downstream units, denoted by a_r with $r = \{1, 2, \dots, R\}$, and $a = 1$ if a_r is readmitted, $a = 0$ otherwise. These three considerations expand B_a to:

$$B_a = B - \left(\sum_{i=1}^I x_i + \sum_{e=1}^E a_e - \sum_{c=1}^C a_c^{elective} + \sum_{r=1}^R a_r \right) + \left(\sum_{n=1}^N d_n + \sum_{p=1}^P d_p^{early} \right) \quad (3)$$

In a setting without unscheduled arrivals, e.g., in an orthopedic hospital exclusively treating elective surgery patients, (3) would suffice to describe B_a and the discharge decision processes to satisfy $B_a \geq 0$. Note that there still is uncertainty in service time, i.e., the number of ICU inpatient days for each x_i , and thus prediction of $\sum_{i=1}^I x_i$ and $\sum_{n=1}^N d_n$ are prone to uncertainty. Further note that at the start of a day (e.g., between 07:00 a.m. to 08:00 a.m. at our partner hospital), ICU decision-makers might initiate their decision process at (2), and if they foresee that the capacity constraint will not be satisfied at any point in time throughout the day, they will try to satisfy the capacity constraint by balancing $\sum_{c=1}^C a_c^{elective}$, and $\sum_{p=1}^P d_p^{early}$. While we appreciate that past studies must make this assumption for their models, cancellations and planned demand-driven discharges do not happen simultaneously to patient arrival. ICU decision-makers rather anticipate the number of planned ICU admissions according to the

operating room schedule at the start of a day and compare these with the available ICU bed capacity after natural discharges (cf. (2)).

Considering unscheduled or emergency/ urgent patients coming from upstream units, i.e., directly from the emergency department or, by a roundabout route, from the central operating room area, or as transfer-ins from other hospitals, the decision process to satisfy $B_a \geq 0$ becomes more complex. Note that in practice, experienced ICU decision-makers might anticipate unscheduled ICU admissions and thus reserve some ICU capacity by discharging more patients than absolutely needed to satisfy $B_a \geq 0$. Indeed, past studies such as Bai et al. (2021) quantitatively derive exactly how much capacity should be reserved balancing the costs of patient rejection, and demand-driven discharge. In fact, one could consider that the capacity constraint actually is $B_a \geq \sum_{u=1}^U a_u^{ant}$, that available ICU capacities must be at least the total number of unscheduled arrivals/ admissions the experienced ICU decision-maker anticipates on a given day ($u = \{1, 2, \dots, U\}$, and $a = 1$ if a_u^{ant} is anticipated as unscheduled arrival, $a = 0$ otherwise). As it is uncertain how many unscheduled patients will arrive exactly, we additionally define a_v^{add} as the unforeseen unscheduled arrivals in addition to $\sum_{u=1}^U a_u^{ant}$, with $v = \{1, 2, \dots, V\}$ and $a = 1$ if the arrival of a_v^{add} is unscheduled and is not anticipated, $a = 0$ otherwise. Note that decision makers might increase the sum of planned early discharges $\sum_{p=1}^P d_p^{early}$ and/ or the sum of cancellations of elective surgeries $\sum_{c=1}^C a_c^{elective}$ to offset $\sum_{u=1}^U a_u^{ant}$, yet to manage any a_v^{add} , the only lever is to demand-driven discharge a patient in an unplanned manner, denoted by d_q^{early} with $q = \{1, 2, \dots, Q\}$ and $d = 1$ if d_q^{early} is early discharged in an unplanned way, $d = 0$ otherwise.¹

¹ Additionally, one could argue that if a_v^{add} arrived early in the day before surgery has started for the last a_e , decision-makers might also have the option to cancel one additional $a_c^{elective}$. For simplicity, we do not consider this option.

To satisfy $B_a \geq 0$, decision makers then consider that

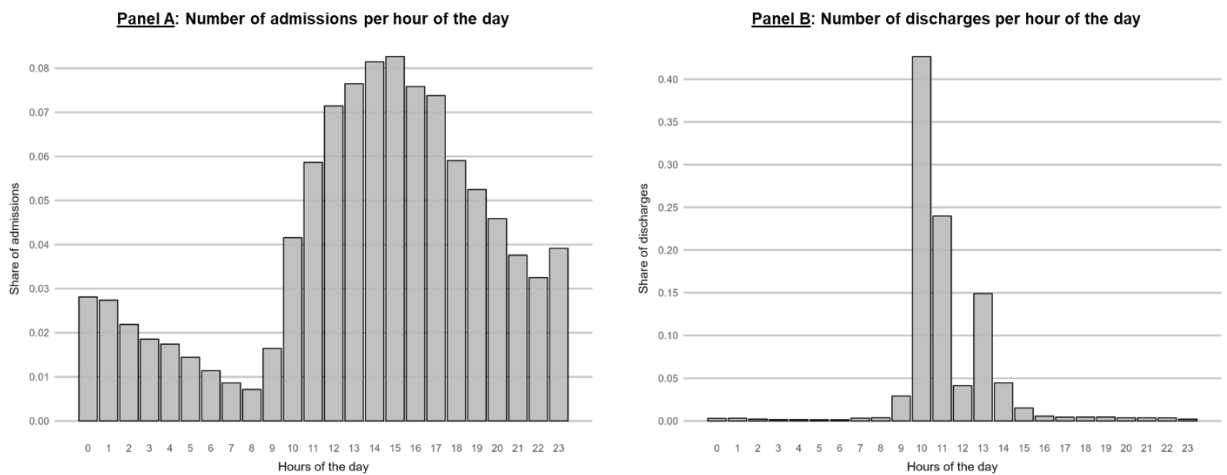
$$B_a = B - \left(\sum_{i=1}^I x_i + \sum_{e=1}^E a_e - \sum_{c=1}^C a_c^{elective} + \sum_{r=1}^R a_r + \sum_{u=1}^U a_u^{ant} \right) + \left(\sum_{n=1}^N d_n + \sum_{p=1}^P d_p^{early} \right) + \left(\sum_{q=1}^Q d_q^{early} - \sum_{v=1}^V a_v^{add} \right) \quad (4)$$

Note that planned discharges, both natural and demand-driven, happen at a later point in time than the discharge decision. At our partner hospital, $\sum_{n=1}^N d_n$ and $\sum_{p=1}^P d_p^{early}$ are decided in the early morning of a (week-) day, while discharges occur in the late morning to early afternoon, in close alignment with the downstream care units admitting the patient(s). Should a patient have worsened between initial discharge decision and actual discharge, decision-makers might re-think and change their initial decision.

Empirical evidence for formal decision constraint

In our data, there is empirical evidence for the dynamics of the decision constraint as formulated in equation (4). Figure 1 shows the typical arrival and discharge patterns at our partner hospital, depicting the share of patients arriving and being discharged per hour of the day.

Figure 2: Discharge (Panel A) and arrival pattern (Panel B) per hour of the day



Annotations: Figure includes all ICU stays of patients with a positive or waived general consent admitted at our partner hospital between January 01, 2016 and December 31, 2023, no exclusion criteria applied (14,121 stays and 12,932 unique cases; cf. Figure 3 below).

Discharges typically occur between 09:00 a.m. and 04:00 p.m. (95% of all discharges), with roughly 86% of all discharges happening in an even closer time window between 10:00 a.m. and 02:00 p.m. This is evidence for the planned discharges decisions $\sum_{n=1}^N d_n$ and $\sum_{p=1}^P d_p^{early}$ happening early in the morning with corresponding discharges a few hours later.

We also see that discharges in “off-hours” between 02:00 p.m. and 10:00 a.m. (14% of all discharges) and especially between 04:00 p.m. and 09:00 a.m. are rather rare (5% of all discharges). We may assume that a considerable share of these discharges are unplanned demand-driven discharges $\sum_{q=1}^Q d_q^{early}$ triggered by unforeseen unscheduled admissions $\sum_{v=1}^V a_v^{add}$. Figure 2 clearly shows that these situations occur comparatively rarely. At the same time, a considerable share of admissions does occur in these off-hours, namely roughly 57% between 04:00 p.m. and 09:00 a.m. This is evidence that – at least in our empirical setting – demand-driven discharges rarely occur as defined in conventional operations research studies.

In sum, roughly 72% of all patients arrive between 10:00 a.m. and 09:00 p.m. Still, the volume of patient admissions (28% of all admissions) between 09:00 p.m. and 10:00 a.m. is not negligible. As described above, the share of discharges in the same time window is quite small. This is evidence that ICU decision makers incorporate planned admissions after surgery $\sum_{e=1}^E a_e$ into their decision making process and that they do anticipate unscheduled admissions $\sum_{u=1}^U a_u^{ant}$ and possibly also readmissions $\sum_{r=1}^R a_r$.

Summary

In summary, we have ascertained three different types of points in time where ICU discharge decisions occur and/ or are changed:

- 1) In the morning in the first hours of a physician’s shift, typically between 07:00 a.m. and 08:00 a.m.
- 2) At any point during the day (and night) if a_v^{add} occurs
- 3) At ICU discharge, should a patient’s health status have considerably changed

In equation (4) we formulate the decision problem for satisfying the capacity constraint $B_a \geq 0$ that decision makers face at each of these three types of points in time. Our model will supply decision-makers at each of these types of points in time with the change in a patient’s readmission risk caused

by a discharge at this point in time. Note that while our model can inform any kind of demand-driven discharge, it also provides decision support for natural discharges. Should the result of our model reveal that the change in readmission risk is too large due to the discharge, the “natural” discharge could be postponed, expecting that additional intensive care might decrease this change in risk.

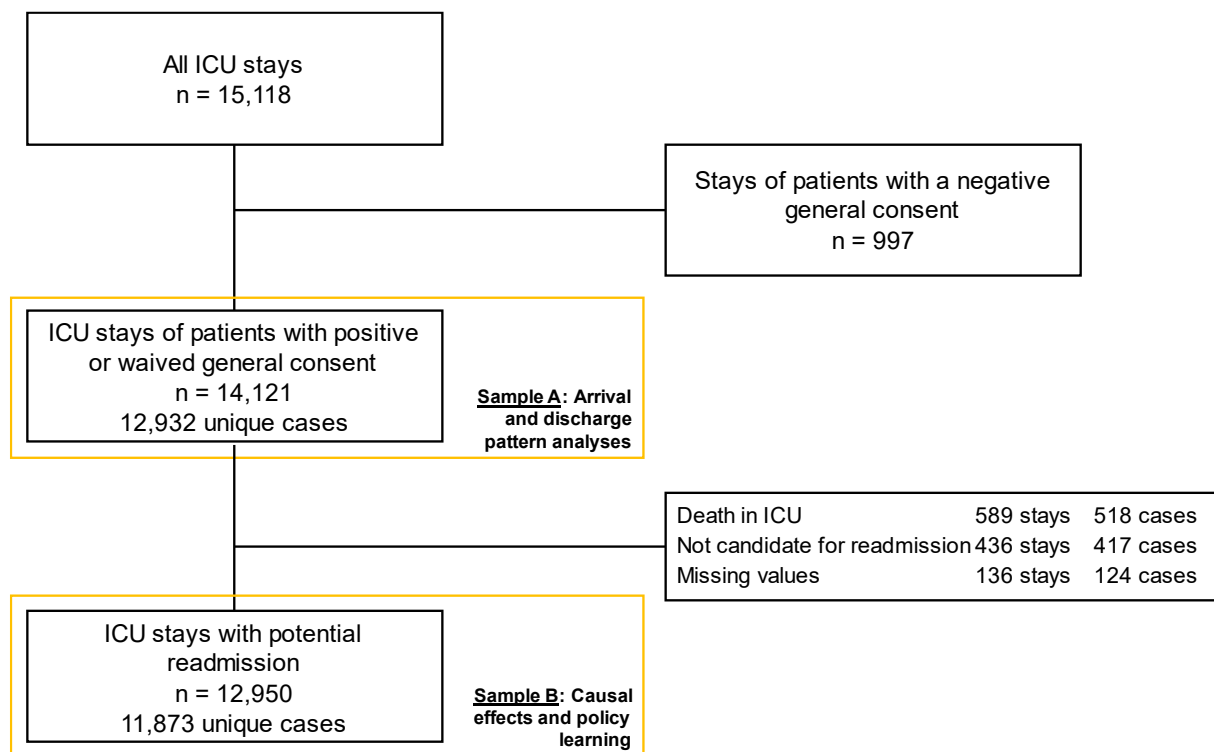
3 Causal Effects and Optimal Policy Learning

We start with a short description of our dataset. Then, we outline a three-step approach to enable optimal policy learning supporting ICU discharge decisions: (1) We present how to estimate the ATE and CATEs of an ICU discharge at a point in time t on the ICU readmission risk in an observational study setting with causal machine learning as basis for policy learning, (2) we outline how we plan to develop decision policies based on HTEs and double-robust scores of individual patients, and (3) we present how we plan to apply these policies to our empiric data to gauge how many ICU bed capacities could have been saved with optimized decisions. In the first section, we also discuss identifying assumptions for causal inference in the specific context of our research endeavor.

Overview of Dataset

Our data is recorded at ICU stay level. Each stay has a unique identifier. One case, given by a unique case number, has at least one ICU stay. Theoretically, one patient could be admitted to a hospital several times in a year. In such cases, a new unique case number would be defined for each hospital stay. A case number for which two or more stays are recorded thus indicates that a patient was readmitted to the ICU within the same hospital stay. Figure 3 shows the inclusion and exclusion criteria and corresponding samples for the different analyses we conducted.

Figure 3: Inclusion and exclusion criteria and corresponding samples



Annotations: Reasons for excluding cases that are not candidates for readmission are discharge to another ICU, to home, to a rehabilitation clinic or nursing home, or to a different hospital (cf. Kramer et al. (2013)).

Sample A was used for analyses regarding arrival and discharge patterns (e.g., Figure 2 above). Sample B includes only those cases and stays that are useable for causal inference. To this end, we excluded patients who died in the ICU as these are recorded as discharges yet are not connected to a deliberate discharge decision, excluded cases that could not be readmitted to the ICU as they were discharged to a different ICU, to home, to a rehabilitation clinic or nursing home, or to a different hospital, and we excluded cases for whom the discharge reason was missing.

Overall, we can extract and engineer more than 4,600 features from our dataset (see Table 1). Most of these features are related to medication and drugs (more than 4,000 features). We include one feature per substance, dosage and volume unit and values represent the given volume (either 0 or a continuous number) within the last 24h prior treatment. Other major feature groups are laboratory diagnostic values (more than 200 features), vital signs (20 features), clinical (risk) scores (close to 100 features) and basic data (age, gender, weight, height, BMI).

Table 1: Overview of used features

Feature category	Number of features	Numeric type	Considered measurements	Description and examples
Medication	4,119	Continuous	Last 24 hours	Hundreds of different substances with at least one, oftentimes several dosages and volume units, e.g., Noradrenalin peripheral in microgram, Noradrenalin in microgram
Laboratory tests	208	Continuous	Last measurement	208 different laboratory values, e.g., Kalium, Creatinin, Cholesterine, HbA1c
Clinical scores	40	Continuous	Last 2 measurements	10 different scores, e.g., SAPS II, SAPS 3, NEMS, GUSS 1, etc.
Diagnoses	114	Dummy	Time invariant	57 indication areas for first and follow-up diagnosis, e.g., "diseases of the liver and biliary tract"
Infusions	35	Continuous	Last 24 hours	22 different infusions, partially with more than one dosage, e.g., Glucose 5%, 10%, 20%, 40%, 50%; all in ml
Ventilation mode	30	Dummy	Last 24 hours	30 different types of (non-) invasive ventilation
Therapies	23	Dummy	Time invariant	23 intervention/ surgery groups, e.g., "orthopedic interventions"
Infections	23	Dummy	Time invariant	22 different infusions, partially with more than one dosage, e.g., Glucose 5%, 10%, 20%, 40%, 50%; all in ml
Vital signs	20	Continuous	Last 4 hours	Mean, SD, and thresholds for blood pressure, body temperature, heart frequency, oxygen saturation
Blood gas analysis	20	Continuous	Last 24 hours	Mean and SD of ten different values
Basic data	5	Continuous (4), dummy (1)	Time invariant	Age, gender, BMI, height, weight
Blood products	3	Continuous	Last 24 hours	Fresh frozen plasma, platelet concentrate, erythrocyte concentrate; all in ml
Total	4,640			

Annotations: BMI = Body-Mass-Index; GUSS = Gugging Swallowing Screen; HbA1c = Hemoglobin A1c value; NEMS = Nine equivalents of nursing manpower use score; mg = milligram; ml = millimeters; SAPS = Simplified Acute Physiology Score; SD = Standard Deviation

Average Treatment Effect Estimation

Potential outcomes framework

To estimate causal effects, we rely on the potential outcomes framework (Rubin, 1974). In an i.i.d. sample, there is a set of patients $i = 1, 2, \dots, n$, each described by a feature vector $X_i \in \mathbb{R}$, a treatment assignment W_i which, in a binary setting, equals 1 if i was treated and 0 otherwise, and an outcome $Y_i \in \mathbb{R}$. The causal effect of a treatment for patient i is given by $Y_i(1) - Y_i(0)$. Accordingly, the average treatment effect (ATE) can be expressed as:

$$\tau = E[Y_i(1) - Y_i(0)] \quad (5)$$

However, for each i only one state $Y_i = Y_i(W_i)$ can be observed. To make progress in observational studies, unconfoundedness (also referred to as selection on observables or conditional independence assumption (CIA) (Lechner, 2001)) is assumed and must be fulfilled (Rosenbaum and Rubin, 1983):

$$\{Y_i(0), Y_i(1)\} \perp W_i \mid X_i \quad (6)$$

With unconfoundedness, it is assumed that treatment W_i is quasi random, given that we control for X_i .

In other words, the potential outcome Y_i is independent of the assignment of the treatment W_i , conditional on X_i .

With unconfoundedness, the ATE can be expressed as:

$$\tau = E[\mu_1(X_i) - \mu_0(X_i)] \quad (7)$$

where

$$\mu_w(x) = E[Y_i \mid X_i = x, W_i = w] \quad (8)$$

To estimate $\hat{\tau}$, we can learn $\hat{\mu}_1(x)$ and $\hat{\mu}_0(x)$ from our data and calculate:

$$\hat{\tau} = \frac{1}{n} \sum_{i=1}^n (\hat{\mu}_1(X_i) - \hat{\mu}_0(X_i)) \quad (9)$$

To estimate $\hat{\tau}$, one could employ a common parametric model such as Ordinary Least Squares (OLS) regression. OLS regression is accurate and consistent as well as unbiased if the underlying linear model is well specified and if its assumptions hold. If the conditional response functions $\mu_w(x)$ are of a non-linear form or if the model's functional form suffers from misspecification, however, parameter estimates will inhibit bias (Wooldridge, 2010).

Non-parametric estimators and (augmented) inverse propensity weighting

Causal forest is a non-parametric machine learning method (Athey et al., 2019; Athey and Imbens, 2016, 2019, 2017; Chernozhukov et al., 2018; Wager and Athey, 2018). Specifically, a random forest (Breiman, 2001) is used to predict $\hat{\mu}_w(x)$, and thus ultimately $\hat{\tau}$. Random forests converge slowly, however, and thus performance with finite samples might still inhibit some bias. Thus, propensity scores, i.e., the probability of receiving treatment based on X_i , are used to weigh $\mu_w(x)$ (inverse-propensity weighting, IPW).

The propensity score $e(x)$ is defined as (Rosenbaum and Rubin, 1983):

$$e(x) = p(W_i = 1 | X_i = x) \quad (10)$$

Under unconfoundedness, the ATE from (5) can then be restated as:

$$\tau = E[Y_i(1) - Y_i(0)] = E \left[\frac{W_i Y_i}{e(X_i)} - \frac{(1 - W_i) Y_i}{1 - e(X_i)} \right] \quad (11)$$

While both outcomes $Y_i(1)$ and $Y_i(0)$ can never be observed for the same unit, the propensity score can and so can (11) be calculated for any i . The unbiased oracle IPW estimator for the ATE is then given by:

$$\hat{\tau}_{IPW}^* = \frac{1}{n} \sum_{i=1}^n \left(\frac{W_i Y_i}{e(X_i)} - \frac{(1 - W_i) Y_i}{1 - e(X_i)} \right) \quad (12)$$

The different author groups listed above have shown (and/ or provided solutions) that the rate of convergence when using machine learning methods, e.g., random forest, to predict $\hat{e}(X_i)$, yielding $\hat{\tau}_{IPW}$, will not be $1/\sqrt{n}$ and thus such estimates will still inhibit some bias. A solution for this is double-robustness. With double-robustness, the estimated ATE $\hat{\tau}$ as formulated in (9) is corrected by the inverse-propensity weighted difference of the observed outcome Y_i and the estimated outcome $\hat{\mu}_w(x)$, also referred to as augmented inverse probability weighting (AIPW) (Chernozhukov et al., 2018; Robins et al., 1994):

$$\hat{\tau}_{AIPW} = \frac{1}{n} \sum_{i=1}^n \left(\hat{\mu}_1(X_i) - \hat{\mu}_0(X_i) + \frac{W_i}{\hat{e}(X_i)} (Y_i - \hat{\mu}_1(X_i)) - \frac{(1 - W_i)}{1 - \hat{e}(X_i)} (Y_i - \hat{\mu}_0(X_i)) \right) \quad (13)$$

$$\hat{\tau}_{AIPW} = \frac{1}{n} \sum_{i=1}^n \hat{\Gamma}_i \quad (14)$$

with $\hat{\Gamma}_i$ denoting each patient's individual double-robust score.

In causal forest applications, such as GRF by Wager and Athey (2018) and Athey et al. (2019), $\hat{\mu}_w(x)$ and $\hat{e}(X_i)$ are estimated from data using random forest. For our research purpose, a key advantage of this method is that it has proven efficient in high-dimensional settings, rendering pre-selection of confounders unnecessary (Wager and Athey, 2018). This is especially important for our research endeavor as our dataset includes thousands of detailed features per ICU case and stay (cf. Table 1 above). Discarding parts of these data based on expert or domain knowledge would inhibit the risk that

the “wrong” features are excluded from analysis, while a data-driven feature selection decreases computational efficiency and increases complexity.

Heterogeneous treatment effects

To analyze treatment effect heterogeneity, commonly, one could try to find strata that reduce variation in ATE estimation, i.e., that help to better predict a potential outcome for a sub-group (Imbens and Rubin, 2015). Stratification has limitations, however. In our context, the two most important limitations are (1) that we could not possibly know which of the thousands of features in our dataset might be the best or even among the best strata, (2) that stratification’s data use is rather inefficient, especially if one needs to consider interaction terms, and (3) that two discharge candidates might belong to the same stratified group, rendering a decision whom to discharge of the two, based on the discharge’s effect on readmission, impossible.

With causal forest, Wager and Athey (2018) and Lechner and Mareckova (2024) have provided causal machine learning methods not only for ATE estimation with observational data under the selection on observables assumptions, but also a flexible and efficient approach to estimate IATEs. IATEs are formally defined by:

$$\tau(x) = E[Y_i(1) - Y_i(0) | X_i = x, Z_i = z] \quad (15)$$

While X_i describes the confounders, Z_i comprises the features defining the patients or group of patients an average effect is estimated for. We will estimate the IATEs with the same strategy and approach as the ATE described above.

Treatment definition

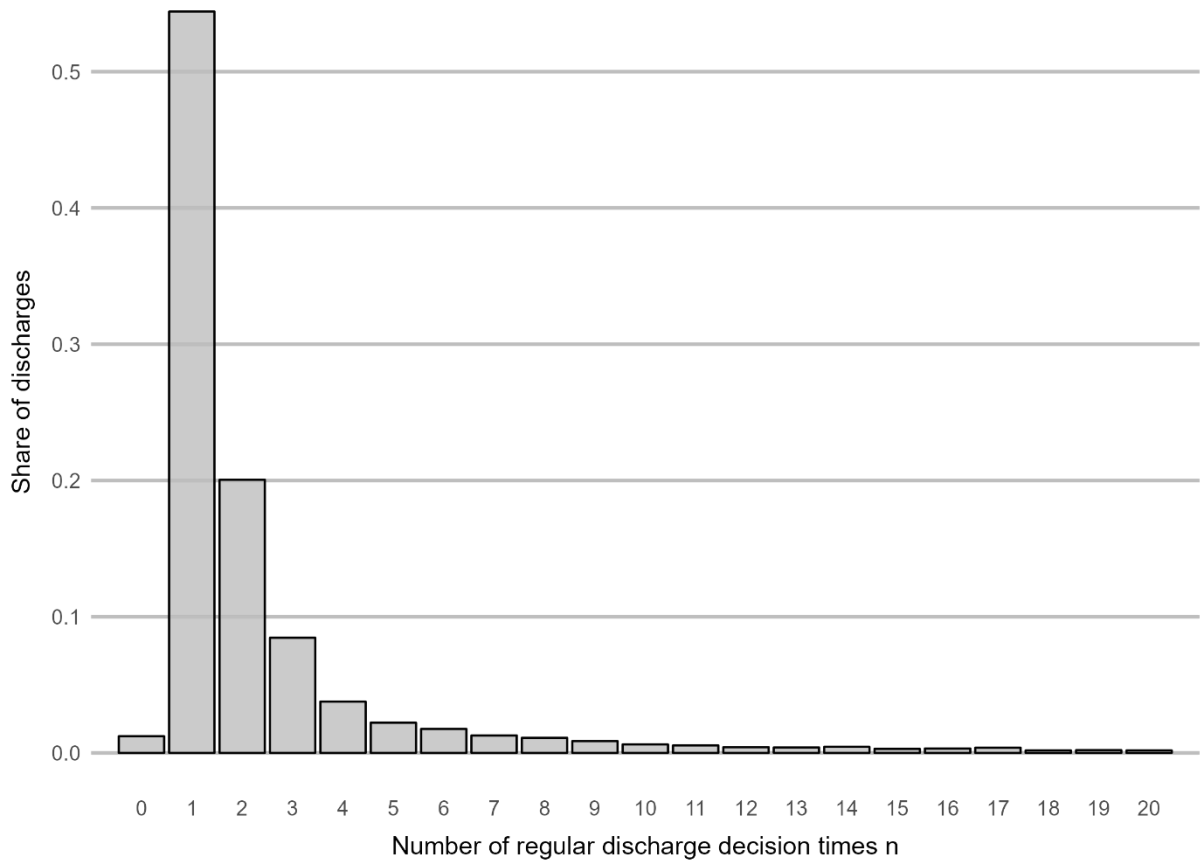
Our treatment is an ICU discharge at point in time t . Each patient admitted to the ICU must be discharged at some point. Thus, a patient’s treatment status at t might be different than at $t + 1$, $t + 2$, etc. To stay in a binary treatment framework, we follow a four-step approach.

Firstly, we define exclusion criteria which indicate that a patient cannot be discharged for medical reasons. These criteria are invasive ventilation and medication with a catecholamine as substance (e.g., noradrenalin) (Heidegger et al., 2005). For each patient in our dataset, we identify the point in time when the last invasive ventilation has stopped and the last dosage of catecholamines has been given.

We add four hours to these identified points in time to approximate the typical time these patients could (theoretically) be discharged. If ventilation has stopped after the last dosage of catecholamines, the ventilation stop plus four hours is marked as the soonest possible discharge and vice versa if the last dosage of catecholamines was later than the ventilation stop.

Secondly, we count how many times a patient passed the regular time when senior physicians decide for a discharge, approximated by 07:00 a.m., after the possible discharge point in time, denoted by n . In our dataset, $n = 1$ for 54% of discharges, $n = 2$ for 20%, and approximately 10% of discharges occur after passing the regular discharge decision time more than five times (cf. Figure 4).

Figure 4: Share of discharges per n



Annotations: n is defined as the number of times a patient passes the regular discharge decision time after becoming a potential candidate for discharge. The plot is based on Sample B (12,950 ICU stays and 11,873 unique cases), limited to all observations with $n \leq 20$ ($n > 20$ is true for 106 ICU stays in our dataset).

Thirdly, we define a random theoretic discharge point in time d of patient i with $d_i = \{\max(n_i - 1, 0), n_i\}$ with equal probability for i to be discharged at $d_i = \max(n_i - 1, 0)$ and $d_i = n_i$.

Lastly, we assign a positive treatment status $W_i = 1$ to all i for which $d_i = n_i$ and a negative treatment status $W_i = 0$ to all i for which $d_i = \max(n_i - 1, 0)$.

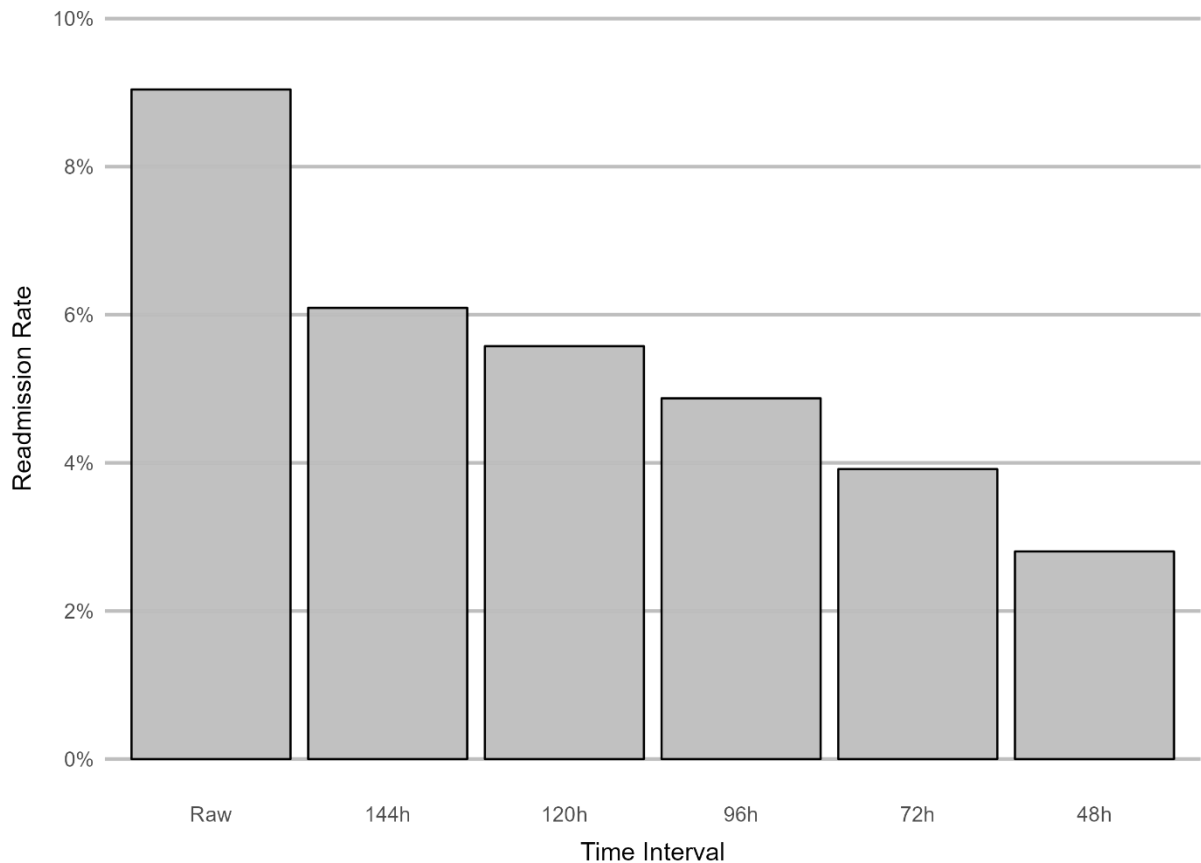
We plan to run this assignment multiple times for separate (I)ATE estimations. Results from each run will be averaged in the end to receive the final results.

Outcome definition

There is an ongoing discussion in the medical literature regarding a meaningful measurement and use of ICU readmission rates (Hosein et al., 2014; Kramer et al., 2013; Woldhek et al., 2017). In our main model, we use readmission regardless of the time between discharge and readmission as outcome. We plan to perform one to two sensitivity analyses, using more narrowly defined readmission rates such as readmission within 48 hours and 144 hours (two to six days).

In our dataset, we observe a raw readmission rate of roughly 9.0% while readmission rates with defined times between discharge and readmission are between 2.8% and 6.1% (see Figure 5).

Figure 5: Readmission rates according to time between discharge and readmission



Annotations: The plot is based on Sample B (12,950 ICU stays and 11,873 unique cases).

Identifying assumptions

Identifying assumptions for causal inference in general and causal machine learning in particular are (Angrist et al., 1996; Imbens, 2000; Lechner, 2001): (1) Unconfoundedness, (2) Common Support (CS) or overlap, (3) Stable-Unit-Treatment-Value Assumption (SUTVA), and (4) exogeneity.

With unconfoundedness, we assume that we observe all variables that might influence both the treatment selection (i.e., to be or not to be discharged at point t) and the potential outcome of a discharge. Discharge decisions are made by senior physicians (Nates et al., 2016). We observe all data and decision variables that are available to these physicians when they make discharge decisions. This includes most variables that were judged by most Swiss ICUs as relevant for ICU discharge decisions (Heidegger et al., 2005). Thus, we argue for unconfoundedness in our study setting. There are three lines of counter-argumentation, however.

The first argument is that situations may occur in which a discharge decision (i.e., our treatment assignment) and thus discharge is determinate. Unconfoundedness would be violated if such a treatment determination was dependent on patient characteristics (X_i). (i) The decision must be positive every time when there is only one patient candidate for discharge at t . We may still assume unconfoundedness, as the number of potential discharge candidates is exogenous, i.e., we can view treatment assignment in these situations still as random. (ii) A discharge decision must be negative if there is a contraindication, e.g., a patient is intubated or a patient receives a certain drug or substance (e.g., catecholamines) (Heidegger et al., 2005). This does not violate unconfoundedness in our context, however, as we always observe the discharge at a point in time when it is not contraindicated (cf. treatment definition).

The second argument is that in practice, physicians actually consider more variables than “only” the thousands of clinical parameters available to them (and to us): Physicians might additionally collect “soft” data, e.g., during daily patient visiting rounds by visual control of the patient and discussions with nurses (Nates et al., 2016; Ofoma et al., 2018). Data obtained this way might include degree of paleness, sweating, communicated pain, mental confusion and disorientation, or therapy compliance.

Soft data is not available to us (or readable by any machine). Unconfoundedness would be violated if these soft data were not correlated with the thousands of clinical parameters available to us. This is rather unlikely.

The third argument is that a discharge, and possibly also a later readmission, are influenced by the available downstream skill mix. Physicians might decide to discharge a certain patient on a given day if they know that there are experienced, well-qualified physicians and nurses in downstream units who can manage the patient, even if this patient is sicker given clinical parameters than another patient who was not discharged another day when downstream skill mix was inadequate. In such situations, physicians might decide against a discharge as they expect a worsening of the patient's health status downstream, rendering an ICU readmission more likely.

To address such doubts that might still remain after controlling for several thousand patient characteristics, we could implement an instrumental variable (IV) approach. An IV approach is available for binary instruments in GRF (Athey et al., 2019) and was developed by Wang et al. (2021) for continuous IVs in causal forests. As IV, we have several options: (1) the daily number of admitted patients as a degree of ICU busyness both as continuous variable (only useable if we can incorporate a continuous IV in GRF) and as dummy (1=busy, 0=not busy; threshold to be determined, e.g., one third of overall ICU capacity), as this has shown to increase the number of ICU discharges (Nates et al., 2016), (2) the number of potential discharge candidates throughout ICU day shifts (e.g., 06:00 a.m. to 08:00 p.m.), or (3) proxies for downstream unit capacity, e.g., weekday vs. weekend, or days until weekend. Regarding (3), actual utilization data would be preferable, yet such data is not collected on a daily level in a digital manner or highly unreliable if collected manually. Note that all three IV options are exogenous of treatment assignment.

For future studies, collecting data on daily downstream skill mix might be perceivable. This comes with considerable effort, however, as such data is not available in a structured manner for all IMCUs and NCUs of a hospital. While staff schedules could be available (often only available in analog form or in e-mails, manually administered Microsoft Excel tables, or similar), these alone will not explain the skill

mix perceived by the ICU decision maker. To accurately account for this perceived skill mix, we would have to label all physician and nurse staff members of all downstream units according to the experience and qualification of all ICU decision makers, which might indeed result in different labels for individual physicians and/ or nurses. Indeed, if experience and skill level are perceived differently by physicians, this might in turn supply an argument that unconfoundedness does hold, as downstream skill mix would not systematically influence treatment assignment and outcome in the same (perceived) way. Lastly, another argument that unconfoundedness still holds is that it is unlikely that a physician will be able to judge the experience and skill level of all treating nurses and physicians active in downstream units, or even that an ICU physician always has full transparency of downstream unit staff schedules. Granted, if a discharge decision for a particularly complex patient were made, a physician could take the time to get transparency over staff schedules and also experience and skill level. A systematic influence still is unlikely, however.

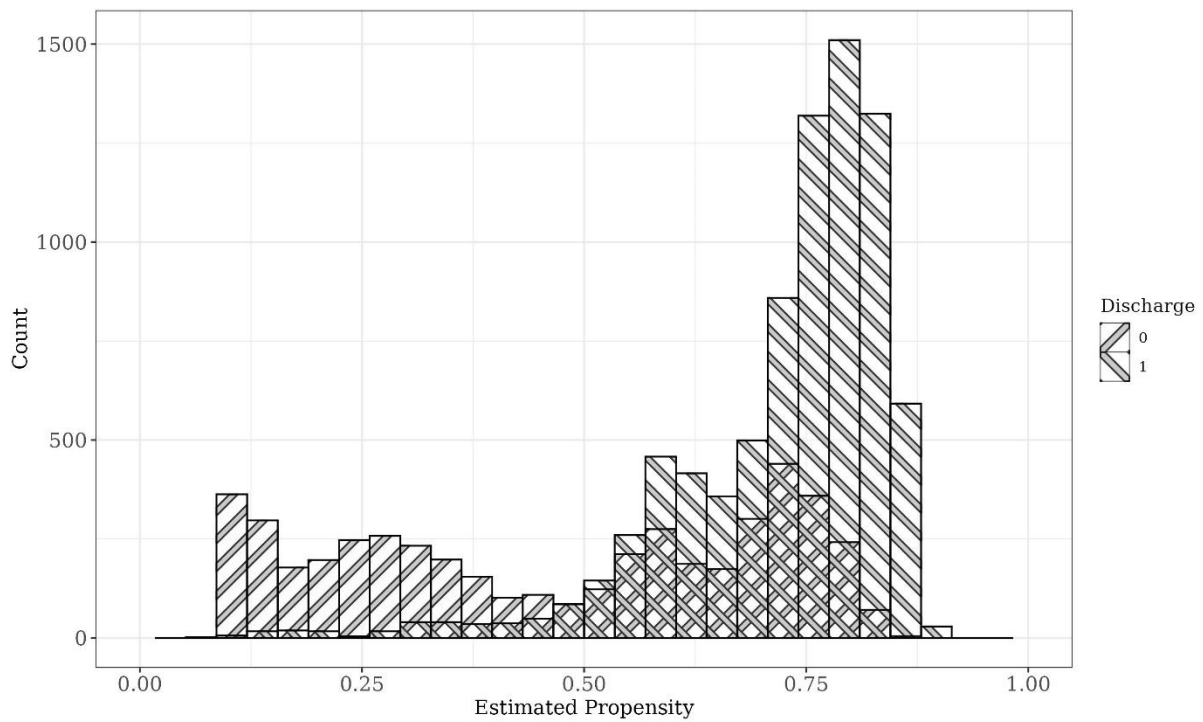
Another possibility could be to measure experience by the number of years a medical professional has been actively working, and qualification by academic degrees, further education certificates, and scientific publications. This approach would also pose a major challenge in terms of required effort, and at least some of these data will not be available in a structured form. Lastly, measuring experience and skill level in this way also has limitations. For instance, one might argue that experience is in fact built by being exposed to adverse events and difficult situations. This will correlate with the number of years a professional has been working but this must not necessarily be true.

We may assume CS, if we can show that propensity scores “overlap”, i.e., that each patient could be observed with or without a discharge at point t :

$$0 < p(W_i = 1|X_i = x) < 1 \quad \forall x \in X \quad (16)$$

In Figure 6, we plot the distribution of propensity scores for our sample (cf. Wager and Athey, 2018).

Figure 6: Common support and overlap analysis of propensity scores



Annotations: Propensities were estimated with GRF, and for Sample B (12,950 ICU stays and 11,873 unique cases).

The plot shows that for our sample and treatment definition, there is a medium to strong selectivity into and out of treatment, respectively. Lechner and Mareckova (2024) show that their Modified Causal Forest (MCF), delivers more robust estimates than GRF in cases of (medium and) strong selectivity, especially when estimating IATEs. Thus, we estimate ATEs with both algorithms, one example of CATEs for exemplification with GRF, and IATEs with MCF.

The SUTVA requires that spillover effects between discharged patients are absent. More concretely, the discharge of one patient can only affect the outcome of the same patient and not the outcome of any other patient. This is given as discharging one patient does not directly influence the readmission risk of another patient. One might argue that once the capacity constraint $B_a \geq 0$ holds, no additional patient(s) is discharged any more, even if this were medically possible, and thus the treatment state of the discharged patient(s) to satisfy $B_a \geq 0$ might influence the treatment state of some of the patients remaining in the ICU. Still, the treatment state of the discharged patient(s) will not directly influence the outcome of the patient(s) remaining in the ICU.

Exogeneity stipulates that patient characteristics used as confounders (X_i) are not influenced by the discharge at point in time t (the treatment). This assumption holds as we observe X_i before the discharge occurs.

In summary, we should be able to fulfill all four identifying assumptions or at least be able to implement an empirical strategy and methods to handle potential violations, ensuring robust ATE and CATE estimation.

First results

In Table 2, we present the ATE estimation, employing both GRF and MCF.

Table 2: Estimated Average Treatment Effects

Algorithm	Estimate	Standard Error	Absolute change of readmission risk (in %-pts.)	Relative change of readmission risk (in %)
MCF	0.00767	0.0083903	0.77	8%
GRF	-0.00179	0.0047603	-0.18	-2%

Annotations: Estimates were made with Sample B (12,950 ICU stays and 11,873 unique cases), >4,600 included features (cf. Table 1). The relative change of readmission risk is calculated in comparison to the raw readmission rate of 9.04%.

The ATE of discharging an ICU patient to a downstream unit one decision point earlier increases the readmission risk by 8% according to MCF, but decreases the readmission risk by -2% according to GRF. Evidently, both point estimates are insignificant, while the standard error for GRF is much larger as compared to the estimate than for MCF. Besides, the magnitude of the effect, regardless of significance and sign of the coefficient, is more than four times higher for MCF than for GRF. Simply put, according to GRF, on average, there is no effect, while the results for MCF imply that there must be individual patients that strongly suffer from an earlier discharge, but also patients that might benefit.

Table 3 shows the estimated CATEs for four groups, stratified by the number of times a patient passes the regular discharge decision time after becoming a potential candidate for discharge, denoted by n . The CATEs show that there is ample treatment heterogeneity. While there is no effect for the group $n = 2$, the magnitude of the estimate is quite large for all other n and standard errors are smaller for $n = 0$ and $n = 1$, but effects are still insignificant.

Table 3: Estimated Conditional Average Treatment Effects according to n

n	Estimate	Standard Error	Absolute change of readmission risk (in %-pts.)	Relative change of readmission risk (in %)
0	-0.01504	0.006106	-1.50	-17%
1	0.01168	0.007846	1.17	13%
2	-0.00097	0.018317	-0.10	-1%
3	0.03302	0.036234	3.30	37%

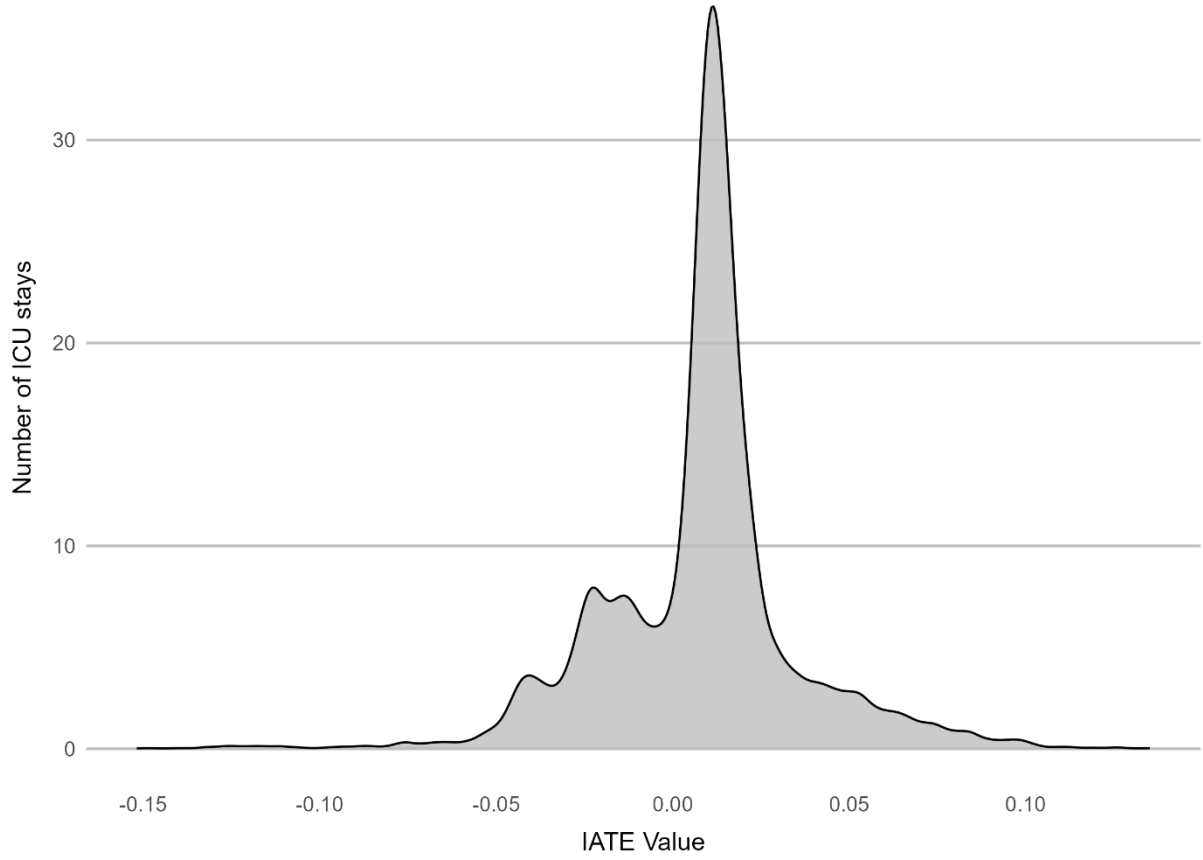
Annotations: Estimates were made with GRF and with Sample B (12,950 ICU stays and 11,873 unique cases), >4,600 included features (cf. Table 1). The relative change of readmission risk is calculated in comparison to the raw readmission rate of 9.04%. n denotes the number of times a patient passes the regular discharge decision time after becoming a potential candidate for discharge.

Note that neither the ATE, nor any kind of CATEs will be of use for decision support. For the ATE, this is obvious as all cases have the same ATE and it thus cannot suggest what patient should rather be discharged. CATEs encompass still too many patients, so that on a given day, two or more discharge candidates might fall into the same group with the same CATE. Then, the same issue as with using an ATE applies.

Therefore, IATEs need to be estimated, forming the basis for developing decision policies that can truly support daily, operational ICU decision making. Given the results in Table 2 and our common support analysis in Figure 6, we chose MCF as causal machine learning method to estimate IATEs. Figure 7 shows the density of estimated IATEs.

Almost the entire sample shows IATE estimates between -0.05 and 0.10 (97.8%, 12,669 ICU stays). Note that this variation is actually a quite: In percentage points, readmission risk is influenced between -5 and 10 points, amounting to a relative change of readmission risk between -55% and 111%. This range shows the existing treatment heterogeneity and showcases that these results could prove effective when developing discharge policies based on IATEs.

Figure 7: Density of Individualized Average Treatment Effects



Annotations: IATEs were estimated with MCF, and for Sample B (12,950 ICU stays and 11,873 unique cases).

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Development of decision policies and simulation study

We aim to design policies offering decision support for all ICU discharge types available to satisfy the capacity constraint $B_a \geq 0$, with B_a as defined in equation (4):

$$B_a = B - \left(\sum_{i=1}^I x_i + \sum_{e=1}^E a_e - \sum_{c=1}^C a_c^{elective} + \sum_{r=1}^R a_r + \sum_{u=1}^U a_u^{ant} \right) + \left(\sum_{n=1}^N d_n + \sum_{p=1}^P d_p^{early} \right) + \left(\sum_{q=1}^Q d_q^{early} - \sum_{v=1}^V a_v^{add} \right)$$

Specifically, policies should offer support when planning discharges $\sum_{n=1}^N d_n + \sum_{p=1}^P d_p^{early}$, and when having to decide in unplanned demand-driven situations described by $\sum_{q=1}^Q d_q^{early} - \sum_{v=1}^V a_v^{add}$. Note that in practice, both d_n and d_p^{early} are planned discharges and distinguishing clearly between what

discharge is natural and what discharge is rather demand-driven due to unplanned but anticipated admissions a_u^{ant} , anticipated readmissions a_r , or planned admissions due to elective surgeries a_e , might be difficult.

In a first step, we will rank all patients according to their IATE estimate. In a second step, we determine that patients should be selected for discharge based on their spot in this ranking. More concretely, if the ICU decision maker were to decide between two patients, the patient with the lower change of readmission risk due to the discharge at point in time t would be selected. The same applies if multiple patients were selected for discharge. For instance, if there are seven discharge candidates and to comply with the capacity constraint $B_a \geq 0$, five patients would need to be discharged, the five patients with the lowest IATEs would be selected according to our decision policy.

To show the practical utility of this approach in terms of avoided readmissions and saved ICU capacity, we will start a simulation at the first day of our observation period. We then apply our decision policy and change the discharge decision for all patients where the policy would discharge a different patient than the patient that was actually discharged. These changes will influence the number of ICU arrivals, as patients are less likely to be readmitted, i.e., $\sum_{r=1}^R a_r$ will be lower. Note that there always remains a minimal risk for readmission, and that we will run the simulation several times. A change in the number of ICU arrival then will lead to different (expected) fulfilment of the capacity constraint $B_a \geq 0$, requiring additional changes in discharge selections.

In our simulation, we will apply decision policies for the first day, then simulate outcomes for the next day, re-apply the decision policies for that day, and finally continue this for all days of the six-year observation period sequentially. We will do this simulation multiple times to increase robustness of results. We sum the simulated observed readmissions per run and average results over all runs, and then finally compare these averages to the actual sum of readmissions. If the simulated sum of readmissions is smaller than the actual, summing the inpatient days of avoided readmissions, we can additionally estimate the number of inpatient days saved by optimal decisions. As a last step, these inpatient days could be transferred into ICU bed capacities with $B = \frac{\text{inpatient days}}{365 \times \text{bed occupancy rate}}$.

4 Summary and Outlook

We outline how optimal decisions can be learned from observational data under the unconfoundedness assumptions, leveraging more than 4,600 features to estimate HTEs of ICU discharge on ICU readmission. Our model addresses a classic hospital operations problem: Decision-making under uncertainty, coupled with fixed capacities, leads to sub-par medical outcomes and bottleneck congestion.

We reviewed the OM literature with regards to machine learning, causal inference, hospital operations, and policy learning, yielding that causal machine learning has rarely been employed in OM, especially in the context of hospital operations. In this working paper, we formulated the decision problem, given by the bed capacity constraint $B_d > 0$, of the ICU discharge process. With two causal machine learning algorithms, GRF and MCF, we estimated ATEs, CATEs and IATEs (the last only with MCF). We described how ranked IATEs can be used in a simulation to show the practical utility of our methodological approach. For the final manuscript of this study, we will implement this simulation. Furthermore, we will explore different IV approaches as sensitivity analyses for scenarios where unconfoundedness might not hold.

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