Vertical Patient Streaming in Emergency Departments

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Tackling hospital emergency department (ED) overcrowding is a paramount challenge for healthcare systems. To combat this issue, an innovative approach is to identify patients who can be served vertically (i.e., in a seated position) and route them to a dedicated area termed the Vertical Processing Pathway (VPP). Successfully implementing this design requires a clear understanding of which patients should be routed to the VPP and when. Currently, the decision on how to leverage the VPP is conducted in an ad-hoc fashion. To assist our partner hospital and other EDs in capturing the value of the VPP, we develop a machine learning model that provides personalized risk scores predicting whether each arriving patient will need an ED bed. We use the derived scores as input to a stochastic patient flow model and analytically characterize the optimal VPP policy that minimizes length of stay. Employing simulation analyses, we identify the settings in which our proposed VPP design is preferable in terms of operational performance to traditional ED flow approaches, such as "fast track" or "physician in triage." Finally, we derive an interpretable VPP patient streaming protocol and conduct a before-and-after experiment where we leverage empirical analyses to evaluate the impact of implementing it in practice. Our findings demonstrate that our protocol is highly effective, leading to significant reductions in patient length of stay without any adverse effect on quality of care measures. Our work results in a VPP protocol that is generalizable to other EDs, offering operational improvements without requiring additional resources.

Key words: Emergency Department, Machine Learning, Operational Efficiency; Vertical Processing; Patient Flow

1. Introduction

Emergency Department (ED) overcrowding has been reported as a major issue of many healthcare systems throughout the past two decades (Schafermeyer and Asplin 2003). The COVID-19 pandemic further aggravated this problem, resulting in significant increases in emergency medicine patient volumes and additional delays and overcrowding to already strained EDs. ED overcrowding is often exacerbated due to the "boarding" problem, where

ED patients who need to be transferred to hospital inpatient units occupy ED beds for long hours, mainly because of lack of bed availability in inpatient units (Saghafian et al. 2023).

Strained ED departments lead to excessive wait times for ED treatment, compromising patient safety, not only within the ED but also throughout the entire healthcare system (Di Somma et al. 2015). ED overcrowding has been shown to cause delays in diagnosis and treatment, leading to poor patient outcomes and quality of care (Association et al. 2002). The repercussions become even more prominent in the cases of critically ill patients, who remain an especially vulnerable population (Derlet and Richards 2002). For those patients who are not critically ill, overcrowding often leads to extremely long waiting times, fueling patient dissatisfaction and walkouts, which can pose a threat to long-term, high-quality medical care (Cowan and Trzeciak 2004). In addition, ED overcrowding causes significant stress and overburden to physicians, increasing the risk of medical errors (Rondeau et al. 2005). It can also lead to ambulance diversion and threaten disaster preparedness (Olshaker and Rathlev 2006).

A direct way of addressing ED congestion is to deploy additional resources (e.g., physicians, nurses, beds, or testing capacity). However, this remains a substantially expensive option that is constrained by physical space and financial resources. Alternatively, healthcare systems make use of advanced technology such as telemedical triage, which allows EDs to offload some of their tasks to physicians who are serving patients in a different hospital (Saghafian et al. 2018). The ED can also choose to "close the doors" through ambulance diversion whenever it lacks the necessary capacity to care for a patient. However, the Emergency Medical Treatment and Labor Act (EMTALA) is very restrictive, prohibiting an ED from diverting an inbound ambulance unless the hospital does not have the staff or facilities to accept any additional emergency patients at that time. Under regular conditions, EMTALA mandates EDs to serve all patients who present to the facility, regardless of their insurance or financial status (Fields et al. 2001). Furthermore, ambulance diversion is not legal in some states, even under congested conditions. Therefore, an attractive approach to address these problems in EDs has been to optimize patient flow processes, which may not require a significant investment in technology or additional resources.

Several studies have demonstrated that optimizing the ED patient flow process can result in significant improvements (Saghafian et al. 2015). Patient streaming, for example, is a well-established ED flow design (Saghafian et al. 2012), which, in its basic format, improves performance by separating and routing patients into distinct streams according to their anticipated disposition. In contrast to pooling, where the same resources treat all types of patients, this type of streaming can lead to improved system efficiency by separating resources for patients who are predicted to be discharged home from ED and those who might require hospital admission post-ED service (Saghafian et al. 2012). Streaming can also be implemented in various other ways, including streaming based on medical complexity (Saghafian et al. 2014), by using a dedicated Fast-Track (FT), implementing a Physician In Triage (PIT) approach, or making use of a Vertical Processing Pathway (VPP) unit (Hodgson et al. 2023). While FT and PIT approaches have been widely adopted by EDs worldwide, VPP remains a hybrid, ad-hoc design.

A limited set of hospitals has already experimented and implemented different forms of the VPP paradigm (Hodgson and Traub 2020, Hodgson et al. 2023, Wallingford Jr et al. 2018). However, no systematic study has been conducted on the optimal patient flow design of vertical processing pathways. Our analysis aims to address this gap, focusing on guiding EDs on the best ways to use a VPP-based patient flow design. We combine a data-driven machine learning (ML) tool with a rigorous stochastic patient flow model to characterize the optimal VPP streaming design. Our work resulted in an actionable, simple, and effective VPP streaming protocol that was successfully implemented by the administration at our partner hospital. Before-and-after comparisons of the implementation of our resulted protocol showed a statistically significant reduction in patient length of stay (LOS) without affecting the quality of care. Our study allows us to draw conclusions on how the proposed VPP design needs to be calibrated and implemented in different hospital settings to maximally enhance ED efficiency. To these ends, we use a combination of analytical, ML, empirical, experimental, and simulation models and address the following research questions:

- *Can an ML model be trained to accurately predict (based only on patient information available at triage) whether an arriving ED patient can be served in the VPP without eventually requiring an ED bed?*
- *Given predictions from an ML model and a set of ED characteristics, what patients should be prioritized for routing to the VPP to minimize the expected patient LOS in the system?*

- *For what hospitals does the VPP-based flow design result in enhanced operational efficiency compared to the traditional FT and PIT models?*
- *What is an effective, interpretable, and easy-to-implement VPP streaming protocol? What is the impact that such a protocol can have, if implemented in practice, on operational ED performance and quality of care?*

1.1. Introducing the FT, VPP, and PIT Flow Designs

Before addressing our research questions, it is helpful to first introduce and discuss the key differences between FT, VPP, and PIT patient flow designs. Figure 1 illustrates the patient flow in the ED under these three forms of patient streaming. Table 1 summarizes their main differences in terms of who triages patients, how low-complexity patients are initially determined (i.e., the selection criteria), and whether the selected low-complexity patients are separated from the rest of the patients and assigned to a dedicated queue.

In an FT model, arriving patients are first triaged and assigned an Emergency Severity Index (ESI) from one (most urgent) to five (least urgent) by a triage nurse.[1] Patients with an ESI greater than three are routed to a separate dedicated queue to be treated in a section of the ED called the FT. In some hospitals, FT providers comprise nurse practitioners or physician assistants dedicated to managing patients in that section of the ED. The main idea of the FT design is to avoid having low acuity patients (who often have shorter "processing times") wait behind high acuity ones.

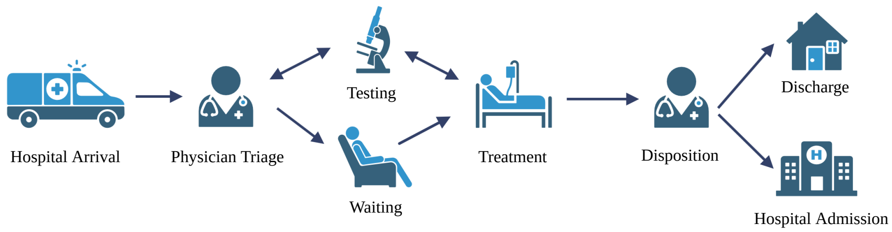
In a PIT model, as the name suggests, a medical provider licensed to order tests and perform the treatment (e.g., physician or advanced practice provider) is assigned to the triage stage working alongside a registered nurse (Franklin et al. 2021). PIT systems essentially provide more flexibility and a higher degree of responsibility to the stage of triage, leveraging medical experts with more advanced training. In addition to assigning an ESI score, (a) ED tests can be initialized during triage, and (b) patients who do not need

[1] In some EDs, patients classified as ESI-1 (and occasionally ESI-2) often arrive via ambulance and are directly taken to a trauma bay or bed where a medical team, rather than just a triage nurse, is awaiting them.

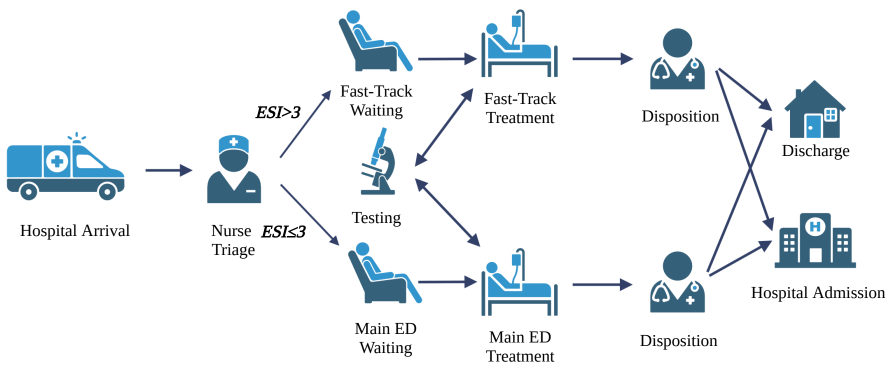
Model	Triage Staff	Assumed Low-Complexity	Dedicated Queue	Test Ordering
FT	RN	ESI > 3	Yes	Yes
PIT	PA/MD	All patients	No	Yes
VPP	RN	Doctor's discretion	No	Yes

Table 1 A Comparison Between FT, VPP, and PIT.

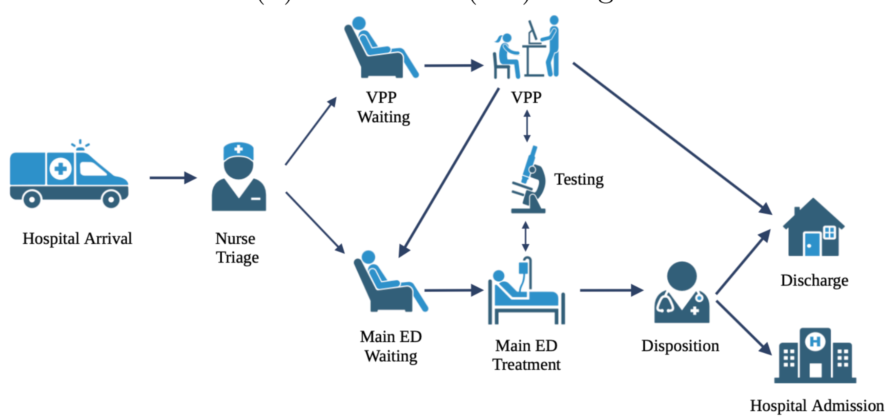
Notes. RN: Registered Nurse, PA: Physician Assistant, MD: Medical Doctor



(a) Physician in Triage (PIT) design.



(b) Fast-Track (FT) design.



(c) Vertical Processing Pathway (VPP) design.

Figure 1 ED patient flow designs.

sophisticated ED care are identified and discharged. Thus, triage providers have the discretion to disposition patients directly. The PIT model has various benefits and drawbacks, as discussed in the literature (Franklin et al. 2021) and has also been implemented in various formats over time (Traub et al. 2015, 2016a). The operational success of such systems depends on local contextual factors, and thus, mixed empirical results have been reported in the literature (Benabbas et al. 2020).

Finally, in the VPP model, as illustrated in Figure 1c,[2] patients are triaged by a nurse who assigns them an ESI level. Upon completion of triage, they are asked to wait to be seen in the main treatment area. Depending on the VPP protocol adopted in the clinic, a patient at triage may be deemed VPP eligible. The attending physician can then evaluate the waiting patient's triage data and determine whether the patient should receive treatment and discharge from the VPP after a quick visit (e.g., 15–20 minutes) without needing an ED bed. If the patient is evaluated in the VPP, but the physician realizes that she needs to be treated on an ED bed, the patient is sent back to the waiting area and is asked to wait until a bed becomes available.[3] Moreover, under the proposed form of streaming, the same patient can be seen multiple times in the VPP as the evaluating physician receives the results of ordered tests and additional examinations. In between the completion of the examination results, patients remain in the waiting room area of the ED since a bed is deemed not necessary for their care.

An important difference between the VPP model and the PIT model is that under the latter, every patient is seen by a physician during triage, and the ED assigns resources to the triage stage to reflect this. In contrast, under the former, only a portion of patients are routed to the VPP because it is not physically equipped or designed to handle all incoming patients: the VPP is suitable for patients who can be served "vertically" as opposed to "horizontally." Put differently, the VPP is only appropriate for patients who do not need an ED bed—the mode of service when a patient is on an ED bed is called "horizontal" since the patient is often laying down. Thus, the VPP design is a patient routing mechanism that relies on upfront predictions of who can be served without needing an ED bed. In contrast, PIT does not involve any prediction-based routing.[4]

Our study demonstrates the value that an optimized form of VPP patient streaming can bring into practice without the need for additional or fully dedicated resources. By serving as a hybrid form of patient flow management, it effectively bridges the gap between the PIT and FT models. Our work showcases how a VPP approach enables EDs to improve

[2] Figure 1c does not capture the specific VPP routing protocol, illustrating only the process the patient follows throughout the ED stay.

[3] When this happens, in the Mayo Clinic, the same evaluating physician remains assigned to the patient so as to limit the rework, which is different from the FT and PIT approaches. However, this practice may vary across past implementations of the VPP in other healthcare systems.

[4] Some systems combine the PIT with an FT. In those cases, an emergency physician determines the ESI score of the patient at triage and their subsequent routing the FT or the main ED.

their operational performance by flexibly capitalizing on the benefits of both pooled and dedicated resources.

1.2. Organization and Summary of Contributions

Our contributions can be summarized as follows:

- We train an ML model on data from our partner hospital to determine a personalized score of VPP eligibility. The model demonstrated robust performance, achieving an Area Under the Receiver Operator Curve (AUC) of 84.6% on the testing set of the derivation cohort. In alignment with medical intuition, it reveals critical associations between patient characteristics and VPP eligibility, such as the role of ESI (positive association), as well as skin, urinary, and eye chief complaints (positive association).
- We combine the ML model with a patient flow model to determine the optimal protocol for utilizing the VPP (based on both the characteristics of the ML model and those of the ED) that minimizes the expected patient LOS in the ED. Our analytical results characterize when and how using a VPP can help ED efficiency as a function of the ML model's discrimination performance and the system's operational status.
- We develop a realistic simulation and calibrate it with hospital data from our partner institution to compare the VPP design with other ED flow designs, such as FT and PIT, in terms of their impact on patient LOS. We find that the VPP design can outperform other flow designs, especially in hospitals where the proportion of low acuity patients is low. Our analyses show that the system's expected LOS under the VPP design is more robust than both the FT and PIT designs due to its adaptive nature to changes in patient population characteristics.
- We derive an interpretable VPP streaming protocol and test its effectiveness by conducting a before-and-after experiment in the newly opened ED of our partner hospital. Our study, which includes three distinct periods of operation (pre-intervention, education, and post-intervention), allows us to empirically evaluate the real-world impact of our proposed protocol. Our results across multiple empirical analyses consistently demonstrate that our proposed protocol can significantly improve ED operational performance compared to an ad-hoc use of the VPP, reducing the system's expected LOS without negatively affecting the quality of care. Our findings showcase the generalizability of our proposed protocol beyond the ED setting of our partner hospital.

The remainder of the paper is structured as follows. Section 2 outlines the related literature. Section 3 describes the study setting at our partner hospital. Section 4 presents a stylized model of the ED flow with a VPP. Section 5 characterizes the optimal policy for VPP usage. In Section 6, we develop and compare ML models that can determine VPP eligibility and illustrate the clinical insights that inform the VPP design. Section 7 compares the optimal VPP design with the FT and PIT flow models, identifying the relative merits of each approach. In Section 8, we derive an interpretable VPP streaming protocol and examine the impact of its real-world implementation on the performance of our partner hospital ED using a before-and-after experiment. Finally, we conclude in Section 9 with a summary of our overall insights from our models and experiments about whether, when, and how a VPP can help EDs improve their performance.

2. Related Literature

There are three main streams of research related to this paper: (1) data-driven models to predict patient flow and outcomes in the ED, (2) queueing models of patient routing within ED operations, and (3) empirical studies in healthcare operations literature focused on interventions in the ED. We briefly highlight the key contributions and findings from each of them below. For a complete review of operations research and management tools applied to ED patient flow, we refer interested readers to Saghafian et al. (2015), and the references therein.

Since the establishment of the Health Information Technology for Economic and Clinical Health Act (US Department of Health et al. 2014), hospitals have been consistently recording the trajectory of the patients within the ED in the form of electronic health records (EHRs). Such abundance of healthcare data has permitted the development of an increasing number of predictive models that attempt to estimate a patient's LOS in the ED. Chaou et al. (2017), Yoon et al. (2003) identified acuity level, age, and the need for additional tests (e.g., laboratory, X-rays, CT scans) as the most predictive factors for a longer LOS using multivariate logistic regression models. Gill et al. (2018) focused on FT patients in the Australian healthcare system to identify the reasons that lead to prolonged LOS. Similar to the previous work, the derived ML model showed that the most important variables are the time taken from a patient's arrival to the time of ordering additional tests, potential admission to the hospital, and bed assignment. These findings indicate that the efficiency of ED streaming processes can be significantly affected when patients with more involved care needs are not appropriately routed. The importance of accurate triage on LOS was also highlighted by Partovi et al. (2001), who showed that a PIT model can offer a moderate decrease in ED LOS, although it is associated with relatively high costs. Nonetheless, there is a high degree of variation in LOS across emergency physicians (Traub et al. 2018), making it a challenging outcome measure to accurately predict at the time of triage.

In addition to LOS, several studies have leveraged data-driven methodologies to predict other patient outcomes associated with ED visits at the time of triage. Hong et al. (2018) used data from three hospital systems to predict hospital admission during ED triage, achieving an out-of-sample AUC of 87%. Raita et al. (2019) developed ML models with equivalent performance on predicting hospital admission and a slightly lower AUC (85%) on predicting intensive care unit (ICU) admission and mortality. Several other studies have been published on predicting mortality at the time of ED arrival either for the entire population or for specific diseases, using triage information (Lee et al. 2020, Bertsimas et al. 2020a, Klug et al. 2020). However, to our knowledge, there has been no study that proposes a validated approach to detect whether a patient visiting the ED will need care on a bed (i.e., "horizontal" treatment) or not (i.e., "vertical" treatment). One of the goals of our study is to address this gap in the literature.

From a queuing perspective, models for improving ED patient flow can be classified based on whether their goal is to reduce boarding times (i.e., delay from when an ED patient is admitted for inpatient care until they physically depart the ED) or to improve patient flow prior to being either admitted for inpatient care or discharged to go home. We refer readers to Feizi et al. (2023), Izady and Mohamed (2021), and (Saghafian et al. 2023) for reviews of the former but focus on the latter in this paper since the VPP has a similar objective.

Most related to our paper are the works of Saghafian et al. (2012, 2014, 2018), Li et al. (2021), and Kamali et al. (2019). Saghafian et al. (2012) uses a combination of a queueing model and simulations to determine when it is optimal to use a disposition-based patient streaming policy in the ED and the conditions under which this policy would result in maximum performance. Saghafian et al. (2014) proposes a complexity-augmented triage algorithm and demonstrates that including an estimation of patient complexity in the traditional ED triage and patient streaming policies results in higher patient safety and lower overall LOS. Saghafian et al. (2018) studies optimal teletriage designs in which ED triage can be done by physicians in other physical locations and highlights the tradeoffs between speed and quality in making patient routing decisions.

Finally, our prospective evaluation of the proposed VPP protocol complements the empirical healthcare operations literature focused on interventions in the ED (Oredsson et al. 2011). Multiple studies have analyzed real-world implementations of patient streaming either in the form of an FT (Kilic et al. 1998, Rodi et al. 2006) or as a PIT system (Travers and Lee 2006, Holroyd et al. 2007). Our study complements the empirical patient streaming literature, constituting the first prospective evaluation of a systematic, data-driven VPP protocol over a controlled time period.

3. Study Setting

To perform our study, we partnered with the healthcare system of Mayo Clinic Arizona, comprising a seven-story facility with 368 licensed beds and 33 operating rooms. At the start of our study, our partner hospital was preparing to open a new building for their ED, where the administration was seeking optimal ways of utilizing a fully operational VPP. We used data from the old ED from October 7th, 2018, until December 31st, 2019, to assist the administration by studying and recommending the best ways of utilizing the VPP. The data from the old ED allowed us to build an accurate ML model (see Section 6), simulation analyses that identify the settings in which the VPP model improves upon the PIT and FT systems (see Section 7), and ultimately derive an interpretable, actionable, and generalizable protocol for use in the new ED (see Section 8). We then measured the impact of our proposed VPP protocol using a prospective before-and-after experiment that took place in the new ED of our partner hospital between February 1st, 2024, until April 30th, 2024. Put together, our analyses allowed our partner hospital to (a) determine an optimal way of utilizing the VPP unit as they moved to their new ED building and (b) observe the impact of implementing it.

The Mayo Clinic review board and our host academic institution approved two protocols for our investigation, characterizing both phases of the study as minimal-risk research and waiving the requirement for informed consent.

We begin with a high-level overview of the two EDs at our partner hospital, which comprise our analyses. Specifically, Section 3.1 describes the operational characteristics of the old ED, while Section 3.2 focuses on the new ED that is currently in operation, where we conducted our before-and-after experiment. Finally, Section 3.3 focuses on the VPP usage that preceded our recommended protocol.

3.1. The Old ED

The old ED at our partner hospital was staffed with board-certified emergency physicians and remained operational until December 8th, 2022. Throughout our initial study period, the ED comprised 26 single treatment rooms and up to nine hallway spaces. To analyze its operations and ground our analysis in a real-world setting, we curated a retrospective dataset of routinely gathered ED operational data from the hospital's electronic health records database. Our dataset comprised de-identified records of all 49,350 patients who were served at the ED between October 7th, 2018, and December 31st, 2019. This time period coincides with the initiation of a new electronic medical record and excludes visits seen during the coronavirus pandemic.

Our data shows that the average LOS in the old ED is 238 minutes, with a standard deviation of 119 minutes (see Table 2). The peak demand hours for the ED were, on average, between 11:00 am and 2:00 pm, similar to the majority of other EDs (Lucero et al. 2021). We observe that 71.94% of the patients who are first seen at the VPP are subsequently assigned a bed in the ED, which shows a low accuracy in the common practice of identifying patients that can be served in the VPP without needing an ED bed (i.e., patients that can be served "vertically" and not "horizontally"). For patients first seen in the VPP, the average (standard deviation) LOS in the ED is 3.82 (2.96) hours. Correspondingly, the average (standard deviation) LOS in the ED is 4.17 (2.83) hours for patients who were not

Variable	Old ED	New ED
ESI	2.8 (0.67)	2.9 (0.7)
Age	55.1 (19.3)	58.9 (21.0)
Visited VPP	6.3% (2.4%)	3.6% (18.7%)
Received ED bed	98% (13%)	97% (16%)
Received ED bed after VPP	72% (45%)	30% (46%)
LOS (mins)	238 (119.4)	259 (122)

Table 2 Summary of Mayo ED records for the two datasets prior to the proposed VPP protocol implementation. We report the mean value and standard deviation in parentheses for both datasets.

Notes: Patients who are 85 or older are listed as 85+ in our data set for privacy protection. The old ED data were recorded between October 7th, 2018, and 31st of December, 2019. The new ED data reflect the pre-trial period of the prospective analysis, spanning from February 1st, 2024, to March 5th, 2024.

routed to the VPP. Figure 2 illustrates the average arrival rate to the main ED as well as the fraction of patients that are routed to the VPP per hour of the day. As indicated in this figure, the VPP was open every day between 7:00 am and 11:00 pm. The exact opening and closing times varied on a individual day basis depending on nursing staff availability.

3.2. The New ED

On the morning of December 8, 2022, the Mayo Clinic ED moved physically to a newly built location connected to the pre-existing hospital, and the previous ED closed. The Mayo Clinic Arizona hospital had experienced increasing ED patient volumes over recent years, so the Arizona Bold Forward initiative included an approximate doubling of ED patient care beds. In anticipation of further increased volumes, our partner hospital hired additional emergency physicians and allied health staff to cover the new beds for the 2022 opening.

The new Mayo Clinic ED contains 56 patient care rooms in a linear rectangular model (see Figure EC.4b), with physicians and allied staff seated in the middle of a long hallway and patient rooms in two long rows along the sides. Unlike the old ED (see Figure EC.4a), no hallway beds exist, so the charge nurses keep a few beds available for critical patient arrivals. Similar to the old ED, patients may be roomed in any area for physicians to see, and patients are assigned to physicians on a rotating basis by a computerized system that removes physician cherry-picking or other patient selection behaviors. Neither ED contains a dedicated fast track, and both remain without a trauma designation. Nurse practitioners, physician assistants, external residents, and medical students may occasionally rotate

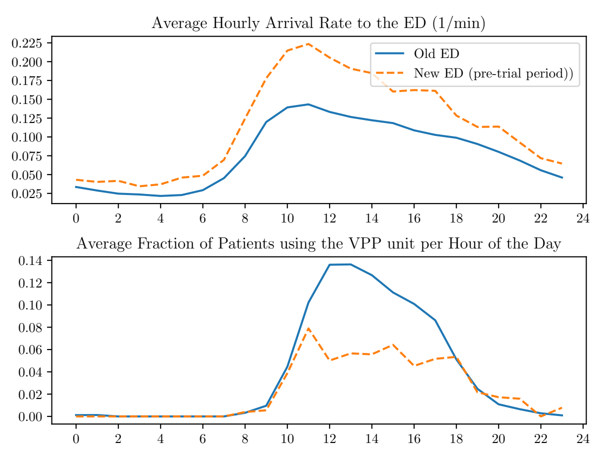


Figure 2 Average hourly arrival rate to the main ED and the VPP in the two datasets.

through the ED but do not practice independently in either the old or the new ED. Neither ED utilizes a physician in triage, instead relying on the assigned physician to place orders on patients early in their ED course.

Finally, as shown in Table 2, the average LOS in the new ED (prior to the implementation of our proposed protocol) is 259 minutes, with a standard deviation of 122 minutes. Similarly, to the old ED, the peak demand hours for the ED were, on average, between 10:00 am and 2:00 pm, but with significantly higher arrival rate (see Figure 2). The age and ESI profile of patients remained similar after the transition. Finally, similar to the old ED, the VPP in the new ED remained closed every day between 11.00 pm and 7:00 am.

3.3. The Past Implementation of the VPP

Prior to the introduction of our proposed VPP protocol, physicians in both EDs identified potential VPP patients from their assigned patient load and contacted a nurse who moved the patient into the VPP room for their assessment. The selection process for the VPP remained ad-hoc within the system, in both the old and the new EDs, and depended on the physician's perception regarding the patient's condition. Specifically, if the physician believed that a given patient in the waiting room can be served without the need for intravenous medication or other types of treatment that required an ED bed, they could request to see the patient in the VPP. Some physicians also used the VPP area not to fully treat and discharge a patient but to initiate a first set of results for those patients who they believed would benefit from an earlier assessment, similar to a PIT system. After being seen in the VPP, patients would return to the waiting room. However, if a bed became available, they were moved to that ED room or a hallway bed.

In the old Mayo Clinic ED, the VPP was a single room with a single patient capacity. It was located next to the waiting area in lieu of another ED ward in close proximity to all the other beds available in the department, as shown in Figure EC.4a. In the new ED facility, the hospital administration dedicated two rooms for VPP usage, as depicted in Figure EC.4b. These rooms are also located next to the waiting area and the triage room to facilitate physical patient flow. For the new ED, the administration sought a redesigned VPP patient streaming design to achieve improved operational performance.

4. An Analytical Model of the VPP Patient Flow

This section aims to characterize the best protocol for using the VPP unit. Since all arriving patients at our partner hospital are randomly assigned to physicians through a rotational patient assignment algorithm, physicians have a fair and equal load of patients. Thus, to gain clear insights, we start by focusing on a single physician who balances her workload between the VPP and the main ED. This modeling decision allows us to gain clear insights into the optimal balance of workload between the VPP and the main ED at an individual level. This is a realistic assumption since once a patient is assigned to the attending physician, individual providers have the discretion to determine the subsequent trajectory of the patient in the ED. In Sections 7 and EC.2-EC.3, we further test the validity of our findings by developing and using a realistic simulation environment calibrated with hospital data.

4.1. Model Description

Patient Flow. The simplified patient-flow diagram for an emergency physician serving arriving patients is depicted in Figure 3, which consists of two main components: the VPP unit and the main ED. Patients arrive with interarrival times drawn from an exponential distribution at a rate of $\lambda \in (0,1)$. For analytical tractability, we start by assuming that the arrival process is time-homogeneous, but we relax this assumption in our data-driven simulation analyses (Section EC.2), where we mimic the actual time-dependent arrival process shown in Figure 2. A fraction of the arriving patients denoted by τ are sent to the VPP unit, and the rest, $(1-\tau)$, are routed to the main ED. The VPP unit and the main ED are assumed to operate with service rates denoted by μ_V and μ_E, respectively.
Without loss of generality, we assume that μ_E is normalized to one ($\mu_E = 1$) and $\mu_V \geq 1$, which reflects the fact that the patients sent to VPP are served much faster than those seen in the main ED area.

A fraction, denoted by $p(\tau)$, of patients sent to the VPP unit will end up needing treatment in the main ED. Effectively, these patients endure the LOS of both the VPP and main ED. Similarly, a fraction of patients denoted by $q(\tau)$ who were sent to the main

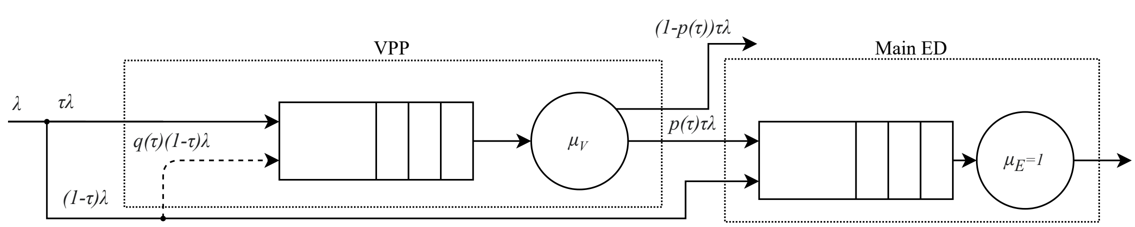


Figure 3 Simplified model of the ED flow with two units: main ED and the VPP.

ED could have been served in the VPP and discharged.[5] We note that $p(\cdot)$ and $q(\cdot)$ are functions of τ, because they depend on the type of patients initially routed to the VPP. We discuss how $p(\tau)$ and $q(\tau)$ depend on τ in Section 4.2 (see, e.g., Equations 7 and 8).

In practice, the patients in the main ED are prioritized and the physician will visit the VPP only when she has idle time. Specifically, apart from occasions in which the main ED queue is empty, idle time could also occur in practice when the physician is waiting for a patient's test results or the patient is administered a lengthy treatment such as an intervenous (IV) drug and requires no direct physician intervention until the treatment is over. In such occasions, although a main ED bed is occupied, the physician can attend to the VPP without compromising the LOS of the main ED patient. In contrast, VPP patients always require physician presence since the VPP is designed for physicians to conduct quick diagnosis and not lengthy treatments. However, the physician might not be available to serve VPP patients at points (e.g., when serving a patient in the main ED). Thus, we assume that the VPP operates as a queue with vacations (i.e., the server cannot serve waiting customers for periods of time), while the main ED operates as a queue without vacations.

In practical terms, this implies that the physician will serve her VPP patients, leave the VPP to perform other tasks (i.e., won't be able to serve VPP patients), and then return to the VPP once again. For tractability, we start our analyses by assuming that all time durations (e.g., service times and vacation times) are exponentially distributed. Under these assumptions, the VPP queue depicted in Figure 3 is an $M/M/1$ queue with exponential vacations. The average waiting time in such a queue, $\mathbb{E}[W_V]$, is calculated in Servi and Finn (2002), which in our setting translates to:

$$\mathbb{E}[W_V] = \frac{1}{\mu_V - \tau\lambda} + u, \tag{1}$$

where u is the average duration of the "vacation." Note that the average vacation length may be a function of how busy the main ED is; namely, if the physician is busy in the main ED she will visit the VPP less frequently. However, we assume that the vacation process, and hence u as the average vacation duration, is exogenous since, in practice, it

[5] In our partner hospital, patients are not routed from the main ED to the VPP unit when there is a realization that the patient could have been served in the VPP unit. However, $q(\tau)$ represents an opportunity cost, which must be considered when deriving the optimal τ.

mainly depends on how frequently on average the physician decides to visit the VPP. In other words, although the main ED patients are prioritized, the priority rule is not such that the VPP is completely omitted during the times in which the main ED is extremely busy.

To find the waiting time in the main ED, we note that it has an arrival stream that is composed of two distributions: a Poisson process with a rate of $(1-\tau)\lambda$ and a non-Poisson process that is based on departures from the $M/M/1$ queue with vacation. Using these two distributions, and benefiting from the results of Tang (1994), we derive the distribution of inter-arrival times to the main ED in Lemma 1.

LEMMA 1. *Let $f_a(t)$ be the distribution of inter-arrival times to the main ED. We have:*

$$f_a(t) = -\frac{\lambda}{(1-\mu_V u)\Big[p(\tau)^2\lambda^2\tau^2u^2-1\Big]} \Bigg[(-1+\tau-p(\tau)\tau)(-1+\mu_V u)e^{(-1+\tau-p(\tau)\tau)\lambda t}+ p(\tau)\tau(\mu_V-\lambda p(\tau)\tau)u(1+(1-\tau)\lambda u)e^{-\big((1-\tau)\lambda+1/u\big)t}+ \mu_V p(\tau)\tau((1-\tau)\lambda+\mu_V)u^2(-1+\lambda p(\tau)\tau u)e^{-\big((1-\tau)\lambda+\mu_V\big)t}\Bigg]. \quad (2)$$

The proof of Lemma 1 and all the other proofs are presented in the Appendix. Note that Equations 1 and 2 denote the actual VPP wait time and main ED inter-arrival distribution, respectively, and not the counterfactual scenarios that would result from considering the $q(\tau)(1-\tau)$ portion of system arrivals that could have been served in the VPP. Equation 2 illustrates how the main ED's arrival stream is a complex and parametric combination of new patient arrivals and those redirected from the VPP. The latter substantially depend on the misclassification rate $p(\tau)$ as well as the VPP queue's average duration u of the vacation. We next use Kingman's approximation for the average wait time of a $G/G/1$ queue to estimate the main ED's average wait time, W_E. Specifically, we have:

$$\mathbb{E}[W_E] \approxeq \frac{\rho}{1-\rho}\Big(\frac{C_a^2+C_s^2}{2}\Big), \quad (3)$$

where $\rho = \frac{(1-\tau)\lambda+p(\tau)\tau\lambda}{1} = (1-\tau)\lambda + p(\tau)\tau\lambda$ is the utilization rate of the main ED, C_a^2 is the squared coefficient of variation (SCV) of inter-arrivals which can be calculated from

Equation 2 ($C_a^2 = \mathrm{Var}[T_a]/\mathbb{E}[T_a]^2$, where T_a denotes the inter-arrival times to the main ED), and $C_s^2 = 1$ is the SCV of service times (recall that the main ED's service time is exponentially distributed). Again, similar to Equations 1 and 2, ρ is defined here for the actual system and not the hypothetical scenario in which the $q(\tau)(1-\tau)$ portion of the main ED patients are also served in the VPP.

REMARK 1. We use the empirical arrivals to the main ED in our data to demonstrate the validity of the distribution derived in Equation 2. Specifically, we sort the actual arrivals to the main ED by physician, then date/time, and subsequently focus on the empirical distribution of arrivals for the time of day with peak arrival rates, 11 am - 12 pm, on each day of the week, separately.[6] As our data does not contain vacation lengths or the specific LOS in the VPP, we estimate these two parameters within reasonable practical ranges and show that Equation 2 matches what we observe from our data using the Kolmogorov–Smirnov (KS) test. The results are shown in Figure EC.5. The p-values from the KS-tests are denoted in the upper plots. They indicate that what we obtain from Equation 2 closely matches our empirical data.

Patients. We assume each arriving ED patient has a true and unknown medical complexity level that can be used for patient streaming (see, e.g., Saghafian et al. (2014)) denoted by $\gamma \in [0,1]$. A patient will need to be treated in the main ED, if their complexity level exceeds a threshold, α. In practice, α represents the baseline prevalence of patients who can be served and discharged directly from the VPP. At our partner hospital, $\alpha = 0.1985$. However, to provide general insights useful for a range of EDs, in our model, we allow for any α satisfying that $0 < \alpha < 0.5$, which considers the reality that in almost no ED more than half of the patients can be treated and safely discharged from the VPP without needing a bed in the main ED.

When patients with $\gamma > \alpha$ are routed to the VPP, they will need a bed in the main ED after their VPP service. Similarly, when patients with $\gamma \leq \alpha$ are routed to the main ED, they could have been discharged from the VPP. Based on these, we next develop a decision support tool that makes use of an ML model, and aids decision-making by determining the best routing policy considering the associated costs of misrouting patients.

[6] We focus on the busiest time of the day because the data density is higher and allows for a better approximation of the distribution.

4.2. A Decision Support Tool

Recall from Figure 3 that VPP patients need to be re-routed to the main ED with probability $p(\tau)$, and main ED patients could have been discharged from the VPP with probability $q(\tau)$. To derive $p(\tau)$ and $q(\tau)$, and hence the associated costs of misrouting patients, we first discuss an ML model that can be used as part of the decision support tool.

Machine Learning Model. We consider an ML that uses up-front patient features (e.g., triage information) to predict for each arriving patient i a class label, $Y_i \in \{0,1\}$, defined as whether they will need a bed in the main ED ($Y_i = 1$) or can be safely discharged from the VPP without eventually needing an ED bed ($Y_i = 0$).

In essence, while the true complexity of the patient (γ) is unknown, the ML model maps the up-front patient information available into a predicted complexity, $\hat{\gamma}$. A threshold of τ is then used to route patients; patients with $\hat{\gamma} \leq \tau$ are sent to the VPP unit and the rest are routed to the main ED. A perfect ML model would predict $\hat{\gamma}$ such that a classification threshold of $\tau = \alpha$ would separate the two classes with 100% accuracy. Specifically, the model would suggest that $\Pr(Y_i = 1|\hat{\gamma})$ is equal to 1 for any $\hat{\gamma} > \alpha$, and is 0 otherwise. For an arbitrary ML model, we assume that the probability of needing a main ED bed is a piece-wise constant function of $\hat{\gamma}$ as stated in Equation 4 and depicted in Figure 4 for $\alpha = 0.199$.[7] Essentially, this models the behavior of any ML model with a non-linear shape (e.g., Sigmoid), in which the highest F1-score is achieved when the classification threshold is set to α.[8]

$$\Pr(Y_i = 1 \mid \hat{\gamma}) = \begin{cases} k_1, & \text{if } \hat{\gamma} \leq \alpha \\ k_2, & \text{if } \hat{\gamma} > \alpha \end{cases} \tag{4}$$

In Equation 4, $k_1 \in (0, 1-\alpha)$ is a constant that describes the model's quality. k_2 is calculated based on the fact that, ultimately, $1-\alpha$ fraction of patients need a main ED bed, regardless of what prediction model is used. Namely:

$$\int_0^1 \Pr(Y_i = 1 \mid \hat{\gamma}) \mathrm{d}\hat{\gamma} = 1 - \alpha \ \therefore \ k_2 = 1 - \frac{k_1 \alpha}{1-\alpha}. \tag{5}$$

It is helpful to discuss the properties of the assumed ML model in Equation 4 for further clarification. First, $k_1 \to 0$ represents a "perfect model" with an Area Under Curve (AUC)

[7] As mentioned earlier, 19.85% of patients are seen in the VPP unit at our partner hospital. Thus, we set $\alpha = 0.199$ in Figure 4.

[8] Recall that α is a threshold level of patient complexity, below which patients do not need a main ED bed. Thus, an effective ML model will separate patients with $\gamma > \alpha$ from those with $\gamma \leq \alpha$.

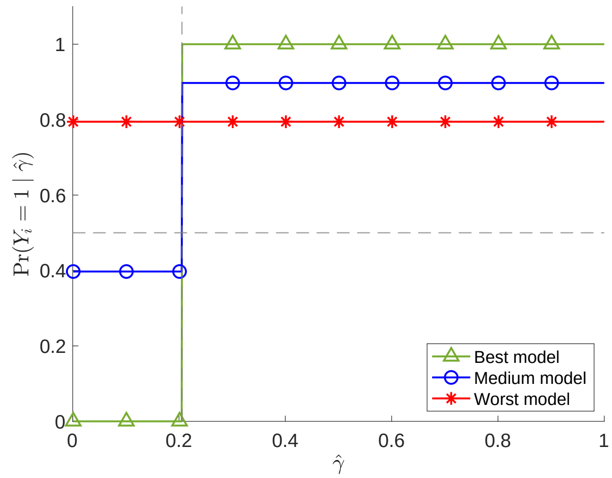


Figure 4 **Probability of needing an ED bed as a function of the estimated complexity score $\hat{\gamma}$.**

of $AUC \to 1$. Conversely, if the model makes predictions randomly (i.e., "worst model") we have $k_1 \to 1-\alpha$ and $AUC \to 0.5$. In the latter case, $\hat{\gamma}$ has no meaningful relationship with γ so the predicted probability of needing a bed in the main ED is equal to the baseline probability for all $\hat{\gamma}$ values. Second, the AUC of the model, in general, can be calculated using Lemma 2.

LEMMA 2. *For any $\alpha \in (0,1)$ and $k_1 \in (0, 1-\alpha)$, we have:*

$$AUC = 1 - \frac{k_1}{2(1-\alpha)}. \tag{6}$$

REMARK 2. While we use k_1 and α as the main ML model parameters, we present the results in Section 5 using an AUC measure for higher clarity. Furthermore, without loss of generality, we may assume that $\hat{\gamma}$ comes from a uniform distribution. Finally, we noted that in practice $\hat{\gamma}$ can be thought of as quantiles, deciles, or any other equal division of the predicted values. For example, if $\tau = 0.15$, this is equivalent to routing the bottom 15% of $\hat{\gamma}$ values to the VPP regardless of the true underlying distribution of $\hat{\gamma}$.

Probabilities of Misrouting ($p(\tau)$ and $q(\tau)$). We state that a patient is *misrouted* if they are sent to the VPP but then needed a main ED bed, or if they were sent to the main ED but could have been seen and discharged from the VPP (i.e., without needing an ED bed). With $\Pr(Y_i = 1 \mid \hat{\gamma})$ defined, we can now derive the system-level conditional probability that a patient needs a bed in the main ED given that she has been routed to the VPP. For a given threshold, τ, $p(\tau)$ is derived in Equation 7.

$$p(\tau) = \Pr(Y_i = 1 \mid \text{VPP}, \tau) = \frac{1}{\tau}\int_0^{\tau} \Pr(Y_i = 1 \mid \hat{\gamma}) d\hat{\gamma} = \begin{cases} k_1, & \text{if } \tau \leq \alpha \\ \dfrac{(\tau-\alpha)(1-\alpha)+\alpha k_1(1-\tau)}{(1-\alpha)\tau}, & \text{if } \tau > \alpha \end{cases} \tag{7}$$

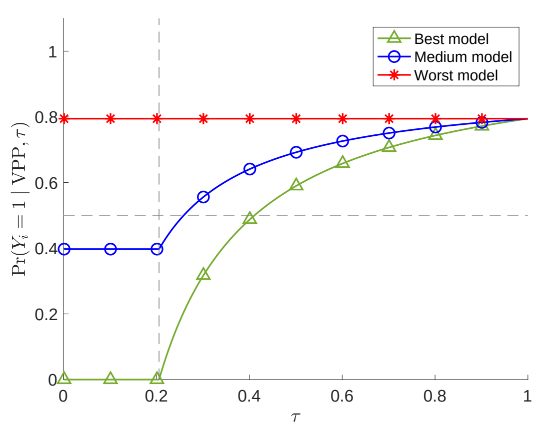
Similarly, the system-level probability that a patient sent to the main ED could have been served in the VPP is given by $q(\tau)$ is derived in Equation 8.

$$q(\tau) = \Pr(Y_i = 0 \mid \text{Main ED}, \tau) = \frac{1}{1-\tau}\int_{\tau}^{1} \Pr(Y_i = 0 \mid \hat{\gamma}) d\hat{\gamma} = \begin{cases} \dfrac{\alpha - \tau(1-k_1)}{1-\tau}, & \text{if } \tau \leq \alpha \\ \dfrac{\alpha k_1}{1-\alpha}, & \text{if } \tau > \alpha \end{cases} \tag{8}$$

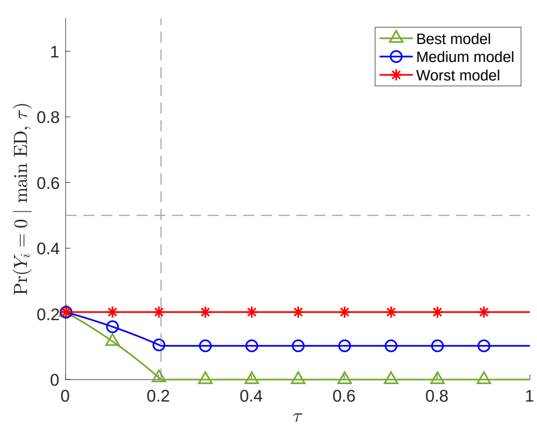
Figures 5a and 5b depict the $p(\cdot)$ and $q(\cdot)$ functions, respectively, for different values of k_1 while setting $\alpha = 0.1985$. Note that with the best model, $k_1 \approx 0$, $p(\alpha) \approx q(\alpha) \approx 0$, as expected; and in the worst model equivalent to random selection, $k_1 = 1-\alpha$, $p(\tau) = 1-\alpha$ and $q(\tau) = \alpha$ which denote the baseline probabilities of needing and not needing a main ED bed, respectively.

4.3. Cost Function

To generate insights into effective routing protocols, we consider a model in which the decision-maker's goal is to minimize the associated costs of misrouting patients with the



(a) Probability of needing an ED bed, given that a patient is served in the VPP.



(b) Probability of not needing a bed, given that a patient is served in the main ED.

Figure 5 Illustration of the $p(\cdot)$ and $q(\cdot)$ functions.

overarching goal of reducing the overall LOS in the ED. The total cost due to patient misrouting is the sum of the additional LOS incurred in the system due to type I and II misrouting errors, which we refer to as the over-utilization and under-utilization of the VPP.

The over-utilization cost is associated with patients who need a main ED bed but are misrouted to the VPP. Since they will be sent to the main ED after being served in the VPP unit, they experience both the LOS of the VPP and main ED. However, they could, ideally, experience only the LOS of the main ED. Hence, the cost associated with over-utilization of the VPP is:

$$C_O(\tau \mid \alpha, k_1, \lambda, \mu_V) = \underbrace{\left(L_V\Big|_{\lambda_V=\tau\lambda} + L_E\Big|_{\lambda_E=(1-\tau)\lambda+p(\tau)\tau\lambda} \right)}_{\text{need main ED bed}} - \underbrace{\left(L_E\Big|_{\lambda_E=(1-\tau)\lambda+p(\tau)\tau\lambda} \right)}_{\text{if routed to main ED}} = L_V\Big|_{\lambda_V=\tau\lambda}, \tag{9}$$

where the term C_O denotes the over-utilization cost, and L_E and L_V represent the LOS of the ED and VPP, respectively. Important to note is that the arrival rate of the ED would not change even if the patients were routed correctly. This is because the patient flow is such that all patients who need treatment in the main ED are eventually routed there. As such, the over-use cost is simplified to the LOS of the VPP.

The under-utilization cost relates to patients routed to the main ED while they could have been entirely served in the VPP. For these cases, the cost function is the difference between their expected LOS in the main ED and that of the VPP. Thus, we have:

$$C_U(\tau \mid \alpha, k_1, \lambda, \mu_V) = \underbrace{L_E\Big|_{\lambda_E=(1-\tau)\lambda+p(\tau)\tau\lambda}}_{\text{could be seen in VPP}} - \underbrace{L_V\Big|_{\lambda_V=\tau\lambda+q(\tau)(1-\tau)\lambda}}_{\text{if routed to VPP}}, \tag{10}$$

where the term $q(\tau)(1-\tau)\lambda$ in λ_V is added because the hypothetical scenario must consider the additional load to the VPP. For a given ML model and set of system parameters, our goal is to find the optimal threshold τ^* for routing patients to the VPP. Note that $p(\tau)\tau$ and $q(\tau)(1-\tau)$ portion of the patients experience the over-use and under-use costs, respectively. Hence, τ^* minimizes the overall cost function and can be written as:

$$\tau^* = \underset{\tau\in[0,1]}{\arg\min}\{p(\tau)\tau C_O(\tau \mid \alpha, k_1, \lambda, \mu_V) + q(\tau)(1-\tau)C_U(\tau \mid \alpha, k_1, \lambda, \mu_V)\}. \tag{11}$$

5. Model Results

In this section, we derive the optimal threshold τ^*, and discuss its main properties. Combining Equations 2 and 3 to gain meaningful insights is mathematically intractable in general. Therefore, in what follows, we first generate insights by assuming that $u = 0$, but relax this in our simulation analyses in Section EC.2.

Solving Equation 11, we can find a unique solution for any given ML model and set of system parameters as stated in the following result.

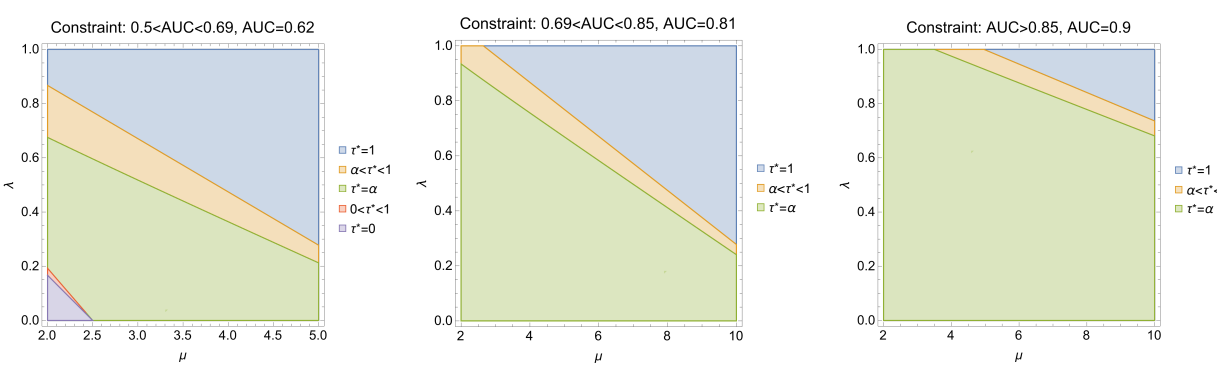
Theorem 1. *For any combination of $(\mu_V, \lambda, \alpha, k_1)$, τ^* defined in Equation 11 is unique and is given in Table EC.1.*

Figure 6 shows the optimal threshold, τ^*, as a function of the arrival rate and VPP service rate, μ_V, for different levels of AUC. Theorem 1 enables us to make several key observations.

Proposition 1. *In the (μ_V, λ) space, denote the region in which $\tau^* = \alpha$ by $\mathcal{A}_k$ for $k_1 = k$. If $k < k'$, then $\mathcal{A}_{k'} \subset \mathcal{A}_k$.*

Recall that a lower k_1 value corresponds to a higher AUC (Equation 6). Proposition 1 states that making use of a better ML model (higher AUC) reduces the need for "risk-taking" for larger combinations of (λ, μ_V), because a higher accuracy in the model essentially means that there is less filtering required at the VPP, and less opportunity cost at the main ED. This implies that the classification threshold that maximizes the F1-score of the ML model (i.e., $\tau^* = \alpha$) is also the optimal operational patient routing threshold for a larger combination of (λ, μ_V) values.

Lemma 3 below describes the relationship between τ^* and the (λ, μ_V) values.



(a) Low-AUC (b) Medium-AUC (c) High-AUC

Figure 6 **Region plots showing τ^* as functions of λ and μ_V for $\alpha = 0.206$.**

LEMMA 3. $\frac{\partial \tau^*}{\partial \mu_V} \geq 0$ *and* $\frac{\partial \tau^*}{\partial \lambda} \geq 0$.

Lemma 3 implies that as the VPP's service rate increases, it becomes optimal to use the VPP for more patients (all else equal). This is because the added LOS due to a (perhaps unnecessary) VPP visit is substantially less than the LOS of the main ED, and thus, the filtering mechanism of VPP in reducing the number of patients sent to the main ED becomes particularly useful. In addition, Lemma 3 states that as the overall arrival rate increases, a greater fraction of patients should be sent to the VPP unit (all else equal). Intuitively, this implies that in hospitals where the arrival rate is high, it is beneficial to overuse the VPP to filter some of the patients who can be discharged quickly—albeit with less certainty—in an attempt to reduce overcrowding in the main ED.

We also note from Figure 6 that for some combinations of parameters $\tau^* = 1$, meaning that all arriving patients should be first routed to the VPP. This implies conditions under which VPP should be used similar to the PIT (see Section 1), and occurs when the ML model's accuracy is below a threshold. Proposition 2 formalizes such conditions.

PROPOSITION 2. $\tau^* = 1$ *if:*

- $\mu_V > \mu_4(k_1, \alpha)$ *for all* λ *and* k_1 *or;*
- $\lambda > \lambda_4(k_1, \alpha, \mu_V)$ *for* $\mu_V > \max(2, \mu_2(k_1, \alpha))$

where $\mu_2(\cdot)$*,* $\mu_4(\cdot)$*, and* $\lambda_4(\cdot)$ *are defined as follows:*

$$\mu_2(k_1, \alpha) = \frac{(1-\alpha)(1-k_1)^2}{k_1}$$
$$\mu_4(k_1, \alpha) = \frac{1-\alpha}{\alpha k_1}$$
$$\lambda_4(k_1, \alpha, \mu_V) = \frac{1-\alpha-\alpha k_1 \mu_V}{(1-\alpha)^2}$$

Proposition 2 describes the conditions under which the VPP unit should be used similar to a PIT model. This occurs when one of the following conditions holds: (1) The service rate of the VPP unit is higher than a threshold, $\mu_4(k_1, \alpha)$, which would justify the incurred LOS penalty of erroneously being served in the VPP with the hope of not having to incur the much longer main ED LOS. Since μ_4 is decreasing in k_1, this implies that as the predictive power of the ML model improves, the VPP must be even faster for it to be optimally used as a PIT. (2) The predictive power of the ML model is better than $k_A(\alpha)$ and the arrival rate is higher than $\lambda_4(k_1, \alpha, \mu_V)$; or (3) The predictive power of the ML model is worse than

$k_A(\alpha)$, the arrival rate is above $\lambda_4(k_1,\alpha,\mu_V)$, and the VPP is faster than $\mu_2(k_1,\alpha)$. The second condition implies that if the arrival rate to the ED increases beyond a threshold, the wait time of the main ED becomes so long that it is optimal to serve all patients in the VPP first with the hope of removing all of those who can be discharged directly via the VPP from the main ED queue. The third condition further implies that when the predictive power of the ML model is worse than $k_A(\alpha)$, the service rate of the VPP must be faster than $\mu_2(k_1,\alpha)$ for the overuse cost to be justified.

The following lemma establishes further insights into the structure of the optimal routing policy.

Lemma 4. *$\frac{\partial \mu_2}{\partial k_1}<0$, $\frac{\partial \mu_4}{\partial k_1}<0$, and $\frac{\partial \lambda_4}{\partial k_1}<0$.*

Lemma 4 states that as the predictive power of the ML model drops (i.e., as k_1 increases), the ED is better off using a PIT model under a wider set of system parameters. In other words, the VPP is useful compared to a PIT model only when it is used in conjunction with an ML model that has decent predictive power. We further test this finding in Section EC.2 using realistic simulation analyses calibrated with hospital data.

Finally, the following proposition establishes conditions under which the VPP unit should not be used (i.e., $\tau^*=0$).

Proposition 3. *$\tau^*=0$ iff $\mu_V<\mu_1(k_1,\alpha)$, $\lambda<\lambda_1(k_1,\alpha,\mu_V)$ and $1/2<k_1<1-\alpha$, where $\mu_1(\cdot)$ and $\lambda_1(\cdot)$ are defined as follows:*

$$\mu_1(k_1,\alpha)=\frac{1}{1-k_1};$$
$$\lambda_1(k_1,\alpha,\mu_V)=\frac{1}{2}\left(2-(1-\alpha)(1-k_1)\mu_V-\sqrt{(1-k_1)\mu_V\left(4\alpha+(1-\alpha)^2(1-k_1)\mu_V\right)}\right).$$

Proposition 3 suggests the following. When a weak ML model is used, patients routed to the VPP are highly misclassified, and hence, need to be sent to the main ED after the VPP visit.[9] In addition, with a combination of low arrival rates and a slow VPP, it is not justifiable to risk routing patients to the VPP, especially when the main ED's LOS is sufficiently low.

In closing this section, we note that Equation 6 and Figure 6 show that for a variety of practical settings $\tau^*\in(0,1)$, meaning that only a proportion of patients should be routed

[9] Recall that under the worst model $p(\tau)=1-\alpha$.

to the VPP unit. In what follows, we make use of hospital data and train ML models to gain further insights into the characteristics of such patients. We then use our findings to design a simple protocol for use in EDs and discuss the results of implementing it at our partner hospital's new ED.

6. Predicting VPP Eligibility Using Machine Learning

Leveraging data from the old ED of our partner hospital, we train and validate ML models that predict, for each arriving patient, whether their care requires a bed in the main ED (probability of needing an ED bed). Our goal is to develop an accurate and generalizable predictive model for VPP eligibility that can be used as input to the analytical model described in Sections 4-5. In this section, we describe the curated dataset, the proposed ML models, and the clinical insights that we obtained from our analysis.

6.1. Data Description

Following standardized protocols across the country, the Mayo Clinic records patient demographic information, vital values, and a chief complaint from each patient. The decision of whether a patient can be examined in the VPP takes place after triage while the patient is in the waiting room. Thus, for the development and validation of the downstream ML models, we leverage only the limited information provided at the time of triage as potential predictors (see Table EC.5). In addition to the clinical information at the time of triage, we received for each patient whether and what type of additional examinations were subsequently performed. We also obtained operational and discharge information regarding the timing and the part of the ED where care was provided. This allowed us to analyze the entire patient trajectory in the ED, and correspondingly calibrate our simulation models in Sections 7 and EC.2.

6.2. Outcome of Interest

The outcome of interest for the target supervised ML model is whether a patient will require a bed at the main ED prior to discharge. From our data, however, we do not observe this variable for patients that *could have been* discharged without needing an ED bed. That is, we only observe in our data patients who are discharged after being seen in the VPP without being assigned an ED bed. However, a percentage of patients who are assigned an ED bed, could have been discharged without it, if they had been initially routed to the VPP (instead of the main ED). For this reason, and based on conversations with emergency physicians, we identify patients that can be discharged without an ED bed using the following criteria:

- **Golden Labels**: Patients who received care at the VPP and were subsequently discharged without the use of an ED bed ($N = 901$).
- **Synthetic Labels I**: Patients with an ESI score of 3 who were treated using an ED bed but were discharged home after their ED visit without being admitted to the hospital. In addition, we require for this population the provision that no intravenous medication or fluids were administered, and neither X-rays, CT scans nor ultrasounds were performed during the ED visit. Moreover, we require that the time from first contact to discharge was at most two hours ($N = 4,034$).
- **Synthetic Labels II**: Patients with ESI scores of 4 or 5 who were treated using an ED bed but were discharged home after their ED visit without being admitted to the hospital. Moreover, we require for this population the provision that no intravenous medication or fluids were administered during the hospital stay since administrating them cannot happen in the VPP ($N = 4,861$).

The above criteria have been developed and validated by the emergency physicians at our partner hospital and are based on clinical insights regarding patients who can be served without being assigned an ED bed. To ensure that the evaluation of the derived ML models was unbiased and objective, we allocated all observations with a synthetic VPP eligibility label in the training set and all observations with the golden labels in the testing set. Thus, we ensure that the reported performance of the derived classifiers in Section 6.3 is not artificial.

6.3. ML Models

Leveraging the data from our partner hospital, we train binary classification models to predict whether a patient's care will require the use of an ED bed. We compare a wide range of well-established ML algorithms, including logistic regression with regularization (to avoid overfitting), classification trees (CART), random forest, gradient boosted trees (XGBoost), support vector machines (SVM), and multi-layer perceptron (MLP) (Hastie et al. 2009, Breiman et al. 2017, Breiman 2001, Chen and Guestrin 2016, Cortes and Vapnik 1995, Rosenblatt 1958). We tune the model hyperparameters by maximizing the K-fold cross-validation AUC using a bayesian optimization framework Head et al. (2020).

To train and objectively evaluate the derived models, we perform bootstrapping by creating multiple training and testing set partitions using the Sciki-learn library Pedregosa et al. (2011). As noted in Section 6.2, all observations associated with no need for an ED bed (VPP eligible) consistently remain in the same set for all bootstrapped partitions since we restrict the golden labels in the testing set and the synthetic labels in the training set. Bootstrapping is conducted for all remaining samples (not VPP eligible) associated with needing an ED bed. The latter are randomly assigned to either the training set or the testing set such that the ratio between positive and negative samples remains the same between the two partitions of each iteration. We compute the average value and standard deviation of the AUC on the testing set for the five random partitions of the data (see Table EC.7).

All algorithms achieve an average AUC above 82%. The performance across the different algorithms is fairly stable. Specifically, as shown in Table EC.7, the best performing algorithm (random forest, AUC=84.58%) differs only by 2.48 percentage points in mean AUC compared to the algorithm with the worst performance (regularized logistic regression, AUC=82.2%). We also observe that there is not much variability in terms of the reported AUC across different splits of the data, as indicated by the standard deviation metric.

6.4. Clinical Insights

We employ the SHapley Additive exPlanations (SHAP) to identify the risk drivers associated with our outcome of interest Lundberg and Lee (2017). We focus on the average SHAP value of the 20 most important feature predictors in our best ML model—XGBoost. We find that lower values of ESI (blue) yield higher SHAP values, suggesting that more acute cases are more likely to need an ED bed (see Figure EC.7). In contrast, the SHAP value increases with higher values (red) of age, suggesting that higher values of age are associated with higher probability of requiring an ED bed. Our analysis indicates that patients that had a chief complaint involving abdominal pain, chest pain, shortness of breath, neurological issues, fatigue, weakness, fever, and gastrointestinal issues are more likely to need an ED bed. In contrast, patients with skin, eye, urinary, and abnormal test results issues as their chief complaints are less likely to require an ED bed. In terms of other triage information, low diastolic, systolic blood pressure values and oxygen saturation increase the chance of needing an ED bed. The opposite trend applies to the cases of low triage pulse rate, respiratory rate, and body temperature. Our findings are in line with other studies who focused on identifying critically ill patients that require significant care using triage information at the ED (Hong et al. 2018, Sun et al. 2011, Raita et al. 2019).

7. What Hospitals Should Introduce a VPP Unit?

To test the validity of the findings obtained from our analytical model from Section 5 and gain deeper insights, we developed a simulation model of the ED flow and calibrated it with retrospective data from two different healthcare systems. The simulation model serves as a realistic virtual test bed of the ED, where we evaluate the effect of different routing, prioritization, and streaming protocols on patients' average LOS and waiting time. In Section EC.2, we describe the simulation development and validation process, including how the analytical model presented can be translated to a dynamic policy for a real-world ED system. Section EC.2.3 presents the edge of the optimized VPP policy compared to three alternative routing rules for the VPP.

In this section, we turn to our third research question: for what hospitals does the best VPP design outperform other ED flow designs such as FT and PIT? To address this question, we leverage data from the Mayo Clinic Arizona to simulate the operations of the old ED, generating counterfactual non-VPP designs, including FT-based and PIT-based streaming approaches introduced in Section 1 (see Section EC.3 for more details about the assumptions we make to simulate performance under these counterfactual designs). Furthermore, since the population of patients served by an ED differs from one hospital to another, we also conduct a sensitivity analysis on the main characteristics of the patient population served by the ED. Thus, we generate insights into when and for which hospitals the VPP design is advantageous.

Table 3 compares the impact of FT, PIT, and our proposed VPP design which uses $\tau^*(\hat{\gamma})$ (see Section EC.2.3) on the LOS across all patients served, patients served only in the FT/VPP, and patients served in the main ED. In addition, to generalize our insights beyond the context of our partner institution, we generate synthetic populations of ED patients by altering the distributions of ESI levels. We extend our analysis to account for different distributions of the patient population age in Section EC.4. We focus on these two factors, mainly because they constitute two of the most predictive patient characteristics, as shown in Figure EC.7, that are associated with the likelihood of requiring an ED bed. For the feature of patient acuity, we split the synthetically generated patient population

Population	Mean ESI	FT	PIT	VPP
All	2.39	274.7 (273.6, 275.8)	Not Stable	260.8* (259.8,261.9)
	2.76	233.6 (232.7, 234.4)	1277.0 (1253.5, 1300.5)	207.5* (206.6,208.4)
	3.03	Not Stable	260.9 (259.8, 261.9)	209.9* (208.5,211.2)
	3.37	Not Stable	174.0* (173.5, 174.5)	Not Stable
	Mayo ED	232.9 (232.1, 233.8)	785.1 (773.8, 796.4)	204 (201.0,207)*
Main ED	2.39	288.6 (287.5, 289.7)	Not Stable	273.3* (272.3,274.4)
	2.76	249.2 (248.2, 250.1)	1419.1 (1392.9, 1445.4)	233.9* (232.9,234.9)
	3.03	Not Stable	297.2 (296.0, 298.4)	219.9* (218.5,221.3)
	3.37	Not Stable	198.8* (198.2, 199.3)	Not Stable
	Mayo ED	245.6 (244.7, 246.6)	861.4 (848.8, 873.9)	230.3* (229.3, 231.2)
FT/VPP	2.39	96.6* (95.2, 98.1)	Not Stable	119.9* (116.9,122.8)
	2.76	164.6 (163.1, 166.2)	114.9 (113.6, 116.3)	110.3* (108.9,111.7)
	3.03	Not Stable	104.8* (103.9, 105.7)	202.2 (200.1,204.3)
	3.37	Not Stable	99.1* (98.4, 99.7)	Not Stable
	Mayo ED	173.5 (171.9, 175.2)	124.2 (122.8, 125.7)	109.2* (107.2, 111.2)

Table 3 Average LOS and 95% confidence intervals (indicated in parentheses) per patient subgroup across different ED flow designs. Four synthetic patient populations with varying mean ESI scores are considered in addition to the Mayo Clinic baseline sample. We indicate with an asterisk the best performing system for each population subgroup.

into distinct groups based on their ESI level (1 to 5). Subsequently, guided by other ED environments described in the literature, we uniformly sample without replacement from each of the subgroups to generate patient populations of varying severity and care needs that approximate different community profiles that can be served by an ED (Wong et al. 2021, Xu et al. 2009, Araz et al. 2019). We let the mean ESI range from 2.39 and 3.37 (see Table 3), allowing us to present results for EDs where the patient population that might differ from our partner ED.

Overall, our results presented in Table 3 show that given a fixed amount of ED resources, the optimal VPP design outperforms the FT and PIT designs for EDs that serve a patient population with low to medium-high mean ESI scores. However, when the patient body served in the ED has a low prevalence of acute and critical conditions (i.e., involves a low fraction of low ESI level patients), our results suggest that the PIT system is the most suitable design. This is because the flow of patients to the VPP significantly increases as the patient population shifts toward lower acuity patients (higher mean ESI values), rendering the VPP design unstable. This suggests that the VPP design is more suitable for trauma centers or regular teaching hospital EDs, but the PIT system might be the preferred design in community hospitals where a higher fraction of patients are of low acuity. Finally, as shown in Table 3, we find that the FT approach faces the same problem as the VPP design in EDs with a high fraction of low acuity patients. The simulation outcomes also validate the findings from our analytical model: in cases of very high arrival rates to the ED, all patients should be first routed to the VPP, making the VPP and PIT designs similar in their functioning and performance.

For a given simulation setup (i.e., ESI distribution) and patient streaming approach, we do not observe high variability, as shown by the 95% confidence intervals. However, across different streaming systems, we do observe high levels of variation in the expected LOS of the ED. This is attributed to the fact that we have restricted the number of resources to be constant and equal to those present in the old Mayo Clinic ED at the time the retrospective dataset was recorded. Performance variability is most pronounced in the case of PIT. Although it can outperform the FT and VPP in populations with predominantly low-acuity cases, it becomes unstable and highly inefficient without additional physicians as the proportion of acute cases increases. By keeping the resources constant, we highlight the adaptability of the VPP model in different ED environments and demonstrate its robustness under varying conditions. This can be a particularly valuable feature for healthcare administrators, as it is often very challenging to adaptively change staff and bed resource availability in the ED.

Our sensitivity analysis focused on the age distribution of the patient population, reflected in Table EC.4, confirms these findings. Our results indicate that the VPP patient flow design maintains a relatively stable LOS across varying age demographics, suggesting a higher level of adaptability compared to the FT and PIT. This stability underscores the potential utility of a data-driven VPP approach in managing variations in patient demographics within healthcare systems.

8. An Interpretable VPP Routing Protocol and its Implementation at the Mayo Clinic

To create an implementable VPP routing protocol for EDs, we made use of our findings and designed an interpretable and generalizable tree-based protocol. In collaboration with the administrators, physicians, and nurses at our partner hospital, we worked towards its adoption and seamless integration. To carefully examine its impact, we implemented it at their new ED and ran a 13-week prospective experiment to assess its impact. Section 8.1 presents the generalizable tree-based VPP protocol. In Section 8.2, we overview the experimental study design and the data of the prospective evaluation. Section 8.3 describes the empirical methods we employ to analyze the study outcomes, and Section 8.4 summarizes the results.

8.1. A Generalizable Tree-based VPP Protocol

Implementing the optimal VPP design obtained in the previous sections in a real-world ED setting requires the integration of the ML model in the electronic health records system as well as a dynamic calibration of the respective classification threshold τ as a function of the hourly arrival rate and the staffing level at the ED. Similarly to many hospitals in the US, even though the Mayo Clinic has access to an advanced information system that could potentially allow for this type of ML integration, such efforts require a significant amount of resources and organizational change (Panch et al. 2019).

To mitigate this limitation and to ensure a timely transition to an optimized use of the VPP both in our partner ED and in other EDs, we leverage our findings and develop an interpretable and concise protocol that approximates the optimal policy with high precision while greatly simplifying the decision process. To derive a simple and implementable policy, we apply the CART algorithm (Breiman et al. 2017), which can capture non-linear relationships while providing simple and interpretable visualizations of the final model. Our approach involves the following steps:

1. We complement our data set used to derive our simulation models (see Section EC.2) with an additional variable termed “ED in Overcapacity” based on the operational status of the ED at the triage time of each observation. This follows the definition of “Major Overcapacity” based on the guidelines for activation of overcapacity and saturation plans at our partner hospital (see Table EC.8).
2. We derive a label that determines the suggested policy by our analytical model (see Theorem 1 and Section EC.2.2), assigning to each patient one of the following classes: (1) Route to main ED; (2) Route to VPP (with priority); (3) Route to VPP if the VPP queue is empty. The label captures the suggested route of the analytical policy and acts as the dependent variable for the downstream decision tree model.
3. We train a decision tree model by fitting the CART algorithm to the dataset using as the dependent variable the policy outcome.

Figure 7 illustrates the resulting tree-based protocol approximating the optimal policy. Under this protocol, the medical team would only need to determine a patient’s ESI level, whether they had skin, urinary, or eye complaints, and the operational status of ED to

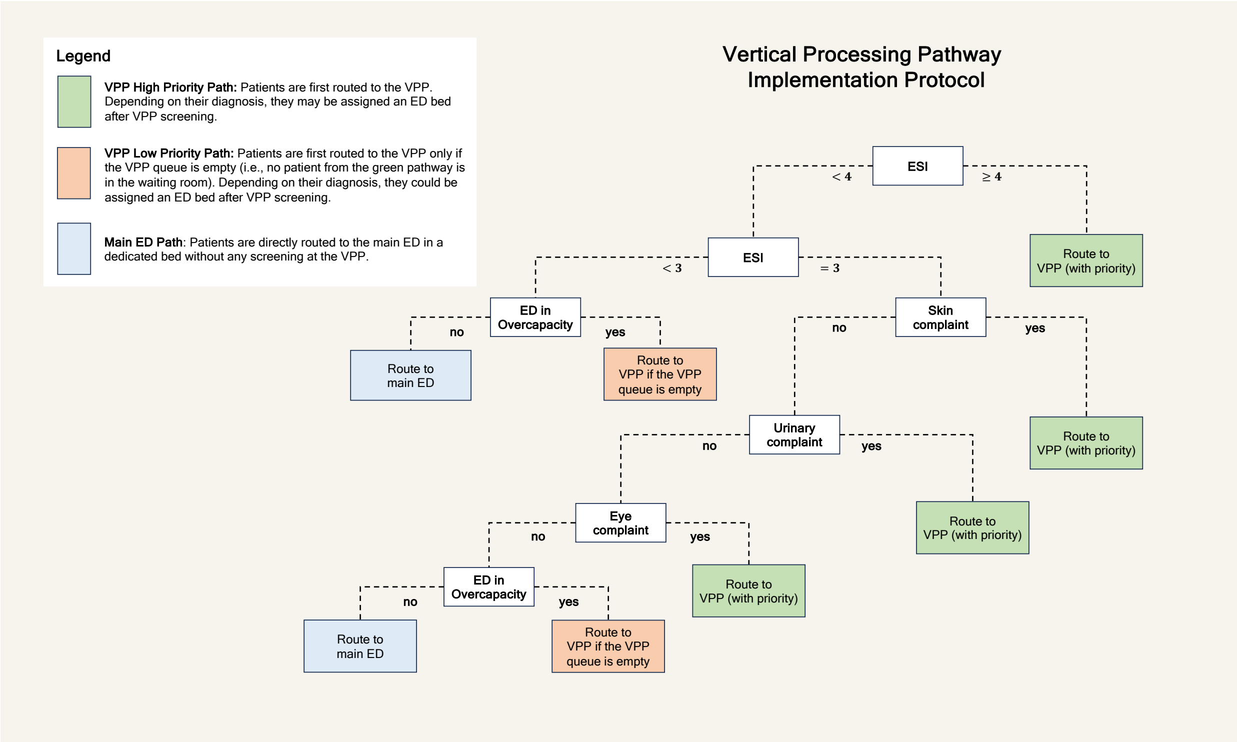


Figure 7 **The tree-based implementation protocol adopted by the new ED at the Mayo Clinic Arizona.**

decide the routing policy for a patient. To summarize, all ESI 1 and 2 patients are sent to the main ED. All ESI 4 and 5 patients are routed to the VPP with priority. ESI 3 patients are routed to the main ED unless they present with eye, skin, or urinary complaints, in which case they are routed with priority to the VPP. Recall that these factors were also found to be most predictive by the XGBoost model (see Section 6.4), indicating that the optimal and approximating policies are aligned. If the ED is in overcapacity status, patients who require an ED bed (e.g., ESI 1-2 patients) can be exceptionally first sent to the VPP if the queue for the vertical pathway is empty to preemptively initiate their treatment.

This protocol was jointly co-developed and validated in several rounds with the medical team. For example, to ensure full implementability, instead of using multiple individual operational characteristics of the ED (e.g., arrival rate and staffing levels), we summarized the ED status with the same definition currently in place in the system at our partner hospital. The resulting protocol is easy to implement, does not require a sophisticated IT system, and yet maintains the high-quality standards of the original optimal policy. Specifically, in out-of-sample computational experiments on the external validation patient cohort, we find that the decision tree model deviates from the optimal policy in only 4.3% of the cases. Moreover, the protocol (see Figure 7) is generalizable and can be used in other

EDs. Notably, the use of ESI values, chief complaints, and operational variables indicating whether the ED is at overcapacity is common among U.S. EDs, making the protocol easy to implement beyond the context of this study.

8.2. Prospective Implementation and Experimentation: Study Design and Data

To measure the effect of utilizing the protocol shown in Figure 7, we conducted a prospective experimental study in the new Mayo ED. Our study occurred between February 1st, 2024 and April 30th, 2024. It involved the following phases: (a) the pre-trial period spanning from February 1st, 2024 to March 5th, during which the ED followed an ad-hoc protocol VPP usage as described in Section 3.3; (b) a three-week educational period taking place from March 6th to March 27th, during which we presented the new patient flow to the medical staff of the ED and conducted regular training sessions for both nurses and physicians; (c) the trial period spanning from March 28th to April 30th, during which the suggested protocol was implemented and the required performance data was collected.

The timeline was selected in such a way as to ensure that the volume, composition, and arrival pattern of patients between the pre-trial and the trial period are similar. Table 4 provides a descriptive summary of the patient records in the pre-trial and trial periods of the prospective study. We curate a patient-level dataset that comprises the pre-trial and trial phases. In our analyses, we exclude all observations from the educational period to ensure an unbiased estimation of the intervention effect. In addition, we limited our sample to the patients seen by physicians who were full-time employees of the new ED in both the pre-trial and trial periods. This results in a final sample of 11,015 patients.

Tables EC.9 and EC.10 summarize the chief complaints reported at triage and attending physician assignments for these periods, respectively. Our results indicate that the distributions of all patient characteristics reported at the time of triage, with the exception of systolic blood pressure and administered medical procedures during the ED visit, are similar between the pre-trial and trial phases. Moreover, patient outcomes, such as disposition post-ED visit and ED return rate (with or without readmission to hospital), also do not significantly differ between the two periods. In addition to ensuring a similar distribution of patient characteristics, the selected timeline allowed the ED to ensure equivalent availability of resources and arrival patterns to the system (see Table EC.11). Of note, nurse

Variable	Pre-Trial (N = 5,522)	Trial (N = 5,493)	p-value
ESI	2.88 (0.66)	2.90 (0.64)	p>0.05
Triage temperature (F)	98.02 (0.80)	98.03 (1.45)	p>0.05
Triage systolic blood pressure	140.32 (25.12)	138.63 (24.80)	p<0.001
Triage diastolic blood pressure	81.41 (13.17)	81.05 (13.91)	p>0.05
Triage heart rate	84.65 (17.75)	84.85 (18.46)	p>0.05
Triage respiratory rate	18.31 (2.77)	18.24 (2.59)	p>0.05
Triage SPO2 %	97.14 (2.58)	97.18 (2.60)	p>0.05
Age	58.92 (20.98)	58.55 (20.92)	p>0.05
Race (white)	88.52%	88.15%	p>0.05
Race (Asian)	2.92%	3.37%	p>0.05
Race (Black or African American)	5.05%	4.81%	p>0.05
Race (unknown)	1.45%	1.18%	p>0.05
Race (other)	2.06%	2.49%	p>0.05
Gender (male)	46.49%	45.69%	p>0.05
Gender (female)	53.48%	54.31%	p>0.05
Gender (unknown)	0.02%	0.00%	p>0.05
Gender (non-binary)	0.02%	0.00%	p>0.05
Ethnicity (Hispanic or Latino)	10.74%	11.34%	p>0.05
Ethnicity (not Hispanic or Latino)	88.32%	87.58%	p>0.05
Ethnicity (choose not to disclose)	0.94%	1.07%	p>0.05
IV	64.98%	65.83%	p>0.05
CT with IV contrast	24.85%	24.63%	p>0.05
CT without IV contrast	19.76%	19.83%	p>0.05
MRI	1.97%	2.06%	p>0.05
Xray	45.60%	44.13%	p>0.05
Ultrasound	11.81%	12.53%	p>0.05
Disposition post ED visit (discharge)	67.08%	66.96%	p>0.05
Disposition post ED visit (hospital admission)	19.30%	18.90%	p>0.05
Disposition post ED visit (hospital observation)	11.86%	12.47%	p>0.05
Disposition post ED visit (transfer to other facility)	1.27%	1.04%	p>0.05
Disposition post ED visit (left against medical advice)	0.47%	0.64%	p>0.05
ED return within 72 hours (with or without admission)?	3.89%	3.84%	p>0.05
ED return within 72 hours with hospital admission?	2.37%	2.17%	p>0.05
ED time from arrival to disposition (minutes)	176.52 (95.05)	168.59 (91.59)	p<0.001
ED time from arrival to departure (minutes)	258.74 (121.88)	247.99 (115.44)	p<0.001

Table 4 Summary of patient records in the pre-trial and trial periods in the new Mayo Clinic Arizona ED. All p-values>0.05 suggest no statistically significant differences between the two periods.

staffing levels are adaptively modified throughout the day as a function of ED occupancy.[10] The distribution of arrival and discharge rates across all time windows did not vary with statistical significance between the two periods.

8.2.1. Dependent Variables Consistent with the objectives of the ED management and the operations management literature, our key dependent variables are two measures

[10] Differences between the pre-trial and trial nurse staffing levels can be attributed to the intervention effect. Our data records do not include the initial nurse schedule for either trial period, and thus, we only observe the staffing levels post-daily adjustments.

of the patient's LOS at the ED: (1) the ED time from arrival to disposition (Feizi et al. 2023); and (2) the ED time from arrival to ED departure (Lim et al. 2024). ED time from arrival to disposition is measured as the time from a patient's arrival to the ED to the time the attending physician indicated the completion of care and either admitted the patient to the hospital or discharged them to return home or be transferred to another healthcare facility. This outcome excludes hospital bed availability from impacting results. ED time from arrival to ED departure measures the total LOS of the patient in the ED, ending when the patient physically departs from the ED. This time includes the boarding time for admitted patients and time to complete paperwork for discharge patients (Feizi et al. 2023). We log-transform the outcome measures because these distributions are close to log-normal (Brown et al. 2005, Saghafian et al. 2023) and right skewed (Song et al. 2015). To complement our primary findings, in Sections EC.7.1-EC.7.2, we also study the effect of the redesigned VPP on quality of care performance metrics. Specifically, we study separately the ED revisit rate with and without admission within 72 hours from ED departure (Lerman and Kobernick 1987). ED returns within 72 hours are often linked to premature discharges, missed diagnoses, or other shortcomings in the initial treatment or discharge plan. As a result, this metric is frequently used as a key indicator of the quality of care.

8.2.2. The Independent Variable The initiation of the trial period on March 28th, 2024, marks the date nurses, advanced care practitioners, and physicians were instructed to consistently use the proposed VPP protocol (see Figure 7). We capture this transition as our independent variable with a binary indicator, which is equal to one if the patient was served during the trial phase of the study and zero otherwise. We exclude from our analyses all patient visits recorded in the educational period.

8.2.3. Independent and Control Variables We control for clinical and operational factors that may affect the dependent variables to best isolate the impact of the independent variable. Our models include variables capturing the patient's condition, the operational state of the ED, and time trends related to the hour of the day. Specifically, we control for (i) patient factors, including ESI, patient age, and primary chief complaint category; (ii) operational factors that may impact the length of treatment, including the physician assignment, whether the patient was admitted for inpatient stay, and the set of diagnostic tests or procedures administered in the ED; and (iii) ED busyness factors, including the number of medical staff present upon the patient's arrival, the number of patients actively receiving or awaiting treatment, and the hour of the day (12 pm - 6 pm, 6 am -12 pm, 6 pm - 12 am) to address systematic variations in treatment length or procedures that may arise from the scheduling of staff across different times of the day.[11]

8.3. Prospective Implementation and Experimentation: Empirical Methods

We use an ordinary least squares estimator with robust standard errors on patient-level data to evaluate the impact of the proposed VPP protocol on our outcomes of interest. The model specification is given in Equation 12 for the outcome of LOS.

$$\log(LOS_i) = \alpha_0 + \alpha_1 trial_i + \boldsymbol{\beta}\mathbf{X}_i + \boldsymbol{\gamma}\mathbf{MD}_i + \boldsymbol{\delta}\mathbf{CC}_i + \epsilon_i, \tag{12}$$

where $\log(LOS_i)$ represents the natural logarithm of the time from arrival to disposition or ED departure, $trial_i$ is the binary dependent variable of the trial period, $\mathbf{X_i}$ is the vector of patient characteristics, $\mathbf{MD}_i$ is a vector of indicators representing the attending physician assigned to patient i, and $\mathbf{CC}_i$ is the vector of patient chief complaint categories. The models for the remaining outcome variables follow the same structure.

One endogeneity concern that may exist arises from selection into treatment. Despite their rigorous training, some physicians may be more reluctant to adhere to the VPP protocol because of their perceived gains in treatment length. Similarly, patients with certain chief complaints may be more (or less) likely to receive the VPP for the same reason. These selection issues may bias our estimates. We address these concerns by applying matching methods to create balanced covariates between the two study periods.

We employ the cardinality matching method proposed by Zubizarreta et al. (2014). It is designed to align treatment and control groups to maximize the matched sample size while minimizing covariate discrepancies between groups. The method can combine different types of matching, including exact matching and fine balancing for categorical variables and moment balancing for continuous variables. It is especially pertinent in complex environments like EDs, where patient outcomes are affected by multifaceted interactions of clinical, operational, and situational factors. By ensuring a rigorous balance of covariates

[11] Unfortunately, due to the privacy requirements of the IRB protocol administered by the Mayo Clinic, we cannot map each patient to a specific calendar date, and thus, we cannot account for time effects related to the day of the week. Nonetheless, our controls for shifts, staffing level, and ED volume capture the differences in demand and capacity that exist across days of each week, especially between weekdays and weekends.

between treated and control groups, cardinality matching can isolate to some extent the impact of an intervention (e.g., implementation of the VPP protocol in our setting), providing more precise insights into their effectiveness.

To perform cardinality matching, we leverage the exact matching option of the algorithm on the ESI level, attending physician assignment, and medical shift at arrival to control for critical factors that directly influence patient treatment pathways and physician decision-making. We apply moment balancing in terms of mean and variance for the number of patients in waiting and treatment since they constitute continuous variables. We employ distributional balancing via fine balance for the number of MDs and nurses on shift, types of procedures and tests administered, and the ED disposition of the patient. Thus, we maintain balance in key operational variables across the matched groups without significantly limiting the data size. The resulting dataset, which we refer to as "Matching on MD," is reduced to $N = 5,158$ observations.

In addition to cardinality matching with exact matching on physician assignment, we provide two additional robustness checks: 1) cardinality matching with exact matching on chief complaint, and 2) propensity score matching. Section EC.6 provides further information regarding the cardinality and propensity score matching process, the respective sensitivity analyses, and resulting datasets.

8.4. Prospective Implementation and Experimentation: Results

Table EC.12 provides a summary of the covariate balance before and after cardinality matching. We present the mean and standard deviation of the sample covariates both before and after the matching process. Before matching, t-tests (continuous variables) and χ^2 tests (binary variables) on the distribution of key variables indicated significant differences, particularly concerning physician assignment. This variation is critical as personal preferences and biases of different physicians can affect adherence to protocols and their implementation. The application of matching was, therefore, essential to mitigate these biases and ensure a fair comparison. Post-matching, the t-tests revealed no statistically significant differences between the matched groups, with the exception of three physicians that attended less than 5% of the cases, and thus, exact matching was not possible, affirming the effectiveness of our matching process (see Table EC.12). The resulting p-values post-matching confirm that our matched sample is well-balanced, reinforcing our confidence that we have successfully generated a sample in which the probability that a patient belongs in the pre-trial or trial periods can be considered random. The standardized mean absolute difference between the pre-trial and trial groups was reduced from 0.0341 (no matching) to 0.0194 and 0.0237 when we performed cardinality matching on physician assignment and chief complaints, respectively, and to 0.0280 in the case of propensity score matching.

Tables 5-6 provide a summary of the regression models for the dependent variables log time from arrival to disposition and ED departure.[12] We report the results for the datasets with no matching and matching on MD. Tables EC.15-EC.16 include the respective results for our sensitivity analyses with matching on CC and propensity score matching. Across all model categories and curated datasets, the trial coefficients indicate a statistically significant reduction in the LOS, with the matched models showing a more pronounced decrease. To measure the expected impact of the protocol on the minute time scale, we exponentiate the derived coefficients of the log transformed outcomes. We find that the expected decrease in the time from arrival to disposition ranges from 3.4% to 5.5% (see Table 5). The actual decrease observed in the clinic was eight minutes (a reduction from 176.52 to 168.59 minutes), equivalent to a 4.5% improvement (see Table 4). Time from arrival to ED departure was consistently associated with an improvement that varies between 2.9% and 4.6% (see Table 6). In the Mayo Clinic ED, we observed a 4.2% reduction, corresponding to a 10.75-minute decrease (a reduction from 258.74 to 247.99 minutes) in LOS during the trial period (see Table 4). The results verify the hypothesis that the proposed VPP design can lead to significant improvements in the ED's expected LOS. They suggest that the VPP protocol leads to more efficient patient assessments and quicker dispositions, optimizing overall ED flow and resource utilization.

[12] A p-value < 0.05 is marked with a single asterisk (*), a p-value < 0.01 is marked with two asterisks (**), and a p-value < 0.001 is denoted by three asterisks (***). All p-values ≥ 0.05 are not marked.

	No matching			**Matching on MD**		
Model	A	B	C	A	B	C
Trial Coef.	-0.044***	-0.042***	-0.035***	-0.057***	-0.053***	-0.053***
	(0.01)	(0.01)	(0.01)	(0.014)	(0.014)	(0.015)
Attending MD	yes	yes	no	yes	yes	no
CC Category	yes	no	no	yes	no	no
Sample size	11,015	11,015	11,015	5,158	5,158	5,158
R^2	0.427	0.414	0.344	0.436	0.423	0.345
F	90.504	131.849	250.779	45.329	64.962	119.053

Table 5 Empirical models summary for the dependent variable "log time from arrival to disposition." The attending MD and CC category rows indicate whether the models controlled for these variables.

	No matching			**Matching on MD**		
Model	A	B	C	A	B	C
Trial Coef.	-0.037***	-0.035***	-0.029***	-0.047***	-0.043***	-0.041***
	(0.007)	(0.007)	(0.007)	(0.01)	(0.01)	(0.011)
Attending MD	yes	yes	no	yes	yes	no
CC Category	yes	no	no	yes	no	no
Sample size	11,015	11,015	11,015	5,158	5,158	5,158
R^2	0.527	0.516	0.477	0.533	0.521	0.481
F	135.005	198.889	435.268	66.48	95.966	208.81

Table 6 Empirical models summary for the dependent variable "log time from arrival to ED departure." The attending MD and CC category rows indicate whether the models controlled for these variables.

Moreover, to ensure that the proposed protocol does not lead to adverse results in the quality of care, we investigated the impact of the VPP protocol on ED quality-related metrics. Tables EC.17-EC.20 provide an overview of the models' findings. None of the models consistently identified any significant effect of the trial on the ED revisit rate. Our results underscore the VPP's effectiveness in managing patient flows without negatively affecting returns to the ED and any additional resources. Our empirical analyses do not indicate any negative impact on patients who were admitted to the hospital or those who were not upon their return to the ED.

The detailed regression output for all models and dependent variables are summarized in the tables of Section EC.7.2. Supplementary analyses assessing the robustness of our results using the Bonferroni correction are presented in Section EC.7.3.

9. Discussion and Conclusions

Our investigation proposes, for the first time, a roadmap on how to design, optimize, and implement a VPP-based patient flow in EDs in a data-driven fashion. By combining ML, queuing, empirical, and simulation analyses, we propose an implementable, interpretable, and near-optimal VPP protocol. We demonstrate its positive impact on ED operations via a real-world prospective experimental study, showcasing the effect of implementing our proposed protocol in practice. Finally, our results provide insights into the conditions and hospitals for which implementing a VPP design outperforms other forms of patient streaming.

Since the benefit of using a VPP largely depends on accurate up-front predictions of patients that can be served vertically (as opposed to horizontally), we started our analyses by introducing an ML-guided VPP design that makes use of patient triage information to determine the degree of VPP eligibility for each patient. However, we recognized that a single ML model for ED bed eligibility in isolation is not sufficient for a successful implementation of a VPP in practice. For this reason, we propose a generalizable analytical queuing model that characterizes the system's optimal policy as a function of ML performance, the patient population characteristics, and the ED's operational load. Our approach considers the patient streaming design holistically, proposing a solution that is not founded on distributional information but on individual patient records. Thus, even though the proposed system is entirely data-driven, its implementation is guided by a rigorous analytical approach that aims to minimize the operational load of the ED. An integral aspect of this analytical approach is that it allows for optimizing ED performance based on three elements: an ED's operational characteristics (e.g., ED service and arrival rates), the patient population the ED serves, and the predictive power of the ML model the ED wishes to implement.

Our analytical approach shows that there exists a classification threshold based on the patient's predicted complexity below which patients should be routed to the VPP. The value of the threshold determines the volume of cases and, thus, the load in the queue of the main ED vis-a-vis the VPP. Our analysis demonstrates that the optimal classification threshold τ^* increases as the overall arrival rate to the ED or the speed of service at the VPP increases. Under low to moderate service and arrival rates in the ED, our analysis reveals that the threshold should be set equal to the baseline, namely the overall proportion of the patient population that can be served without an ED bed. This policy applies to even busier or faster systems as the discrimination performance of the ML improves, which in turn sheds light on the interplay between operations and the quality of the implemented ML model. Of note, when the ED system lies in scenarios of very high arrival rates and the VPP is significantly faster compared to the ED, our policy suggests a "risk-seeking" behavior in which $\tau^* = 1$. Under this setting, all patients become VPP eligible, and the VPP streaming adapts to a PIT streaming approach. Moreover, our sensitivity analysis across different system parameters reveals that the policy regions under the VPP design are fairly robust to time-dependent variations of the arrivals to the ED. Thus, even though the queueing model is time-invariant, the identified optimal policy can be implemented without any concerns related to time-dependent spikes in arrivals.

To facilitate implementing our findings in EDs, we combine our ML and analytical models to derive a tree-based, generalizable VPP protocol, approximating the complex optimal policy in a concise set of guidelines. Our recommended protocol is actionable and concise, approximating the optimal policy with more than 95% accuracy. Thus, it removes the need for EDs to integrate our ML and analytical models with their IT systems. Instead, it allows them to follow a simple set of guidelines to decide whether an arriving patient should be routed to the VPP with high or low priority. After a three-week educational period and only five weeks after its implementation at our partner hospital, the proposed VPP protocol resulted in a 4.5% reduction in patient LOS without requiring any additional resources. Notably, our analyses did not associate the VPP implementation with any adverse effect on established outcomes for quality of care, such as the ED revisit rate within 72 hours. The speed and effectiveness of the prospective trial provide concrete evidence regarding the generalizability, ease of adoption, and operational value of the proposed design.

In addition to demonstrating the benefits of implementing VPP streaming in EDs prospectively, we used simulation analyses to showcase that VPP streaming can lead to substantial improvements in ED efficiency compared to alternative flow designs such as FT and PIT. However, our sensitivity analysis suggests that this finding is not universal. Vertical streaming is most beneficial for EDs with a high proportion of patients of high acuity (low ESI scores). In settings where most patients can be treated with limited tests and resources, the FT has an edge over the VPP approach. We observe, though, that unlike FT and PIT, which require dedicated use of the available resources, the proposed VPP design allows for a more dynamic allocation. This adaptability also stems from the higher degree of decision flexibility given to the individual providers, who ultimately define the patient's trajectory in the ED. This adaptability leads to more resilient system performance with less variation to changes in the patient population characteristics, as shown in our simulation analyses.

These insights were verified during the real-world implementation of the proposed VPP design at the Mayo Clinic. In a past implementation of the PIT system at the same hospital, the clinical team noticed increases in the LOS due to variations in care and hand-offs between providers, often leading to a more extensive workup than if the patient was seen by a single provider. In contrast, upon completing our implementation trial, medical providers highlighted that the proposed VPP protocol runs as a resource-neutral model regarding physician hours. The medical team also noted that while changing between the VPP and the main ED was an interruption in their workflow, it did not interrupt them from seeing higher acuity patients in a meaningful manner. They also observed that due to the improved throughput, the new VPP design allowed them to see higher acuity patients in the main ED in a more timely manner, as low acuity patients who presented to the department earlier in the day were not taking up a room. The latter observations reaffirm some of the core modeling hypotheses in the stochastic system we analyze to derive the optimal VPP policy. Most importantly, a testament to the value of the proposed VPP design is the strategic commitment of the Mayo Clinic ED administration and medical team to expand and further establish its use, aiming to achieve even greater reductions in average LOS beyond the 10.75-minute decrease observed in the trial period.

Limitations and Future Research Directions

Future research could extend our work by fully integrating and testing the ML model and the associated optimal routing protocol or by performing an external validation study at a different institution that serves a dissimilar patient population to the one seeking care at Mayo Clinic Arizona. Further investigations could also include running a prospective study concurrently at two similar EDs or utilizing an experimental design closer to a fully randomized trial. Such a study design would not only enhance the robustness of the findings by comparing changes over time between the two settings but also facilitate the precise recording of waiting times, thereby providing a deeper understanding of the operational impact of the VPP protocol. Future research could explore the impact of other key ED resources, such as nursing staff and VPP room availability, on the VPP model, as well as investigate further some of our modeling assumptions in the stochastic system, such as non-stationary arrival rates or a non-exponential service process that accounts for behavioral factors that influence physician productivity. Alternative VPP designs could also be centered around bed capacity and physician workflow to provide a more comprehensive understanding of the constraints and interactions between physician availability and bed capacity, potentially leading to integrated strategies that optimize both resources. Last but not least, while our models are physician-centric, we recognize that the potential impact of nursing shortages on the implementation and effectiveness of a VPP protocol could be significant. In our setting, neither the old nor the new Mayo ED faced shortages in the nursing staff during our study. However, we acknowledge that the availability of these medical providers remains a critical factor in the success of any patient flow optimization strategy.

We believe these future studies are important next steps. Nevertheless, our work provides promising initial results, showing that various EDs should view the VPP design as an effective yet inexpensive solution for enhancing their operational performance. Importantly, VPP implementation only involves using a dedicated room with limited physical space and no additional expensive resources (e.g., ED bed or added physician), posing minimal constraints compared to the other forms of patient streaming. Furthermore, our proposed protocol removes any need for changes to (or integrations with) hospital IT systems. As such, we hope to see a broader set of experimentation and potential adoption across various EDs in the near future.

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Electronic Companion

EC.1. Proofs

All proofs for equations, theorems and lemmas, where applicable, are given below.

Proof of Theorem 1

If $u = 0$, the LOS of the main ED, LOS_E, then becomes the sojourn time of an $M/M/1$ queue since its arrival follows an exponential distribution with rate λ_E, and can be calculated as follows:

$$LOS_E = \frac{1}{1-\lambda_E}.$$

In addition, note that in reality, $\mu_V >> 1$ because the average time spent in the VPP is in the order of $\sim$ 10 minutes, while that of the ED is $\sim$ 200 minutes. Therefore, although the VPP is an $M/M/1$ queue (with no vacation), we can further simplify the VPP by assuming that it is an $M/M/\infty$ queue with a service rate of μ_V. This is essentially the equivalency of an $M/M/1$ queue with an $M/M/\infty$ queue when the rate at which customers arrive is much less than the service rate, and therefore, practically, a queue rarely forms. In this case, the LOS of the VPP, LOS_V, is:

$$LOS_V = \frac{1}{\mu_V}.$$

Hence, the overuse and underuse costs defined in Equations 9 and 10, can be reduced to Equations EC.1 and EC.2, respectively.

$$C_O(\tau \mid k_1, \lambda, \mu) = \frac{1}{\mu_V}. \tag{EC.1}$$

$$C_U(\tau \mid k_1, \lambda, \mu) = \frac{1}{1-(1-\tau+p(\tau)\tau)\lambda} - \frac{1}{\mu_V} \tag{EC.2}$$

Substituting Equations EC.1, EC.2, 7 and 8 in Equation 11 yields the total cost function to be minimized, C_T:

$$C_T(\tau \mid \alpha, k_1, \lambda, \mu_V) =$$

$$\begin{cases} -\dfrac{\alpha\lambda+\mu_V}{\lambda\mu_V}+\dfrac{\tau}{\mu_V}+\dfrac{1-(1-\alpha)\lambda}{\lambda\Big(1-\lambda+(1-k_1)\lambda\tau\Big)}, & \text{if } \tau\le\alpha \\[2ex] \dfrac{A+B\tau+C\tau^2}{\mu_V\Big(-1+\alpha+\lambda+\alpha\lambda(-2+\alpha+k_1-k_1\tau)\Big)}, & \text{if } \tau>\alpha \end{cases} \tag{EC.3}$$

where:

$$\begin{aligned} A &= -\alpha\Big(-1+\alpha+\lambda+\alpha(-2+\alpha+k_1)\lambda+k_1\mu_V\Big) \\ B &= \Big(-1+\alpha+\lambda+\alpha(-2+\alpha+k_1+\alpha k_1)\lambda+\alpha k_1\mu_V\Big) \\ C &= -\alpha k_1\lambda \end{aligned}$$

The τ that minimizes Equation EC.3 is the optimal fraction of patients that must be routed to the VPP.

We begin by ensuring that C_T is convex for all combinations of $(\alpha, k_1, \lambda, \mu_V)$ in their allowable range. We verify that:

- C_T is continuous at $\tau=\alpha$;
- $\partial^2 C_T/\partial\tau^2 \ge 0$ in both $\tau\le\alpha$ and $\tau>\alpha$ (i.e., second-order condition).

Thus, the function is continuous and convex for all parameters. Next, we find the first-order condition (FOC) that minimizes C_T. We do this separately for $\tau\le\alpha$ and $\tau>\alpha$. For notational convenience, we define:

$$C_1(\tau\mid\alpha,k_1,\lambda,\mu_V) = -\frac{\alpha\lambda+\mu_V}{\lambda\mu_V}+\frac{\tau}{\mu_V}+\frac{1-(1-\alpha)\lambda}{\lambda\Big(1-\lambda+(1-k_1)\lambda\tau\Big)}, \quad \tau\le\alpha$$

$$C_2(\tau\mid\alpha,k_1,\lambda,\mu_V) = \frac{A+B\tau+C\tau^2}{\mu_V\Big(-1+\alpha+\lambda+\alpha\lambda(-2+\alpha+k_1-k_1\tau)\Big)}, \quad \tau>\alpha$$

Case 1: $\boldsymbol{\tau\le\alpha}$

Setting $\partial C_1/\partial\tau=0$, we obtain a unique solution for that minimizes C_1:

$$\tau_1^* = \frac{1-\lambda}{(-1+k_1)\lambda}+\sqrt{\frac{(-1+\lambda-\alpha\lambda)\mu_V}{(-1+k_1)\lambda^2}}, \tag{EC.4}$$

where τ_1^* exists when the following conditions hold:

$$0 < \alpha < \frac{1}{2} \quad \text{(for all } \alpha\text{'s)}$$
$$\frac{1}{2} < k_1 < 1 - \alpha$$
$$2 < \mu_V < \mu_1$$
$$\lambda_1 < \lambda < \lambda_2,$$

where μ_1 and λ_1 are defined in Proposition 3 and λ_2 is defined as:

$$\lambda_2(\alpha, k_1, \mu_V) = \frac{2 - \alpha(-1+k_1)(-2+\mu_V) + (-1+k_1)\mu_V}{2\Big(1-\alpha(1-k_1)\Big)^2} - \frac{-\sqrt{(-1+k_1)\mu_V\Big(4\alpha k_1(-1+\alpha-\alpha k_1) + (1-\alpha)^2(-1+k_1)\mu_V\Big)}}{2\Big(1-\alpha(1-k_1)\Big)^2}$$

Outside of the range where the FOC has a unique solution, τ_1^* is either 0 or α, which we determine based on whether $\partial C_1/\partial \tau$ is positive or negative. This algebra yields the following boundary solutions when $0 \leq \tau \leq \alpha$:

$$\tau_1^* = \begin{cases} \alpha, & \text{if} \quad 0 < k_1 < \frac{1}{2}, \quad \text{since} \quad \partial C_1/\partial\tau \leq 0 \\ \alpha, & \text{if} \quad \mu_V > \mu_1, \quad \text{since} \quad \partial C_1/\partial\tau \leq 0 \\ 0, & \text{if} \quad 0 < \lambda < \lambda_1, \quad \text{since} \quad \partial C_1/\partial\tau \geq 0 \\ \alpha, & \text{if} \quad \lambda_2 < \lambda < 1, \quad \text{since} \quad \partial C_1/\partial\tau \leq 0 \end{cases} \tag{EC.5}$$

Case 2: $\tau \geq \alpha$

Setting $\partial C_2/\partial\tau = 0$, we obtain

$$\tau_2^* = \frac{-1+\alpha+\lambda+\alpha\lambda(-2+\alpha+k_1+k_1\sqrt{-\frac{(-1+\alpha)(1+(-1+\alpha)\lambda)\mu_V}{\alpha k_1 \lambda^2}})}{\alpha k_1 \lambda}, \tag{EC.6}$$

where τ_2^* exists when the following conditions hold:

$$0 < \alpha < \frac{1}{2},$$

$$0 < k_1 < 1 - \alpha,$$
$$\max\{2, \mu_2\} < \mu_V < \mu_4,$$
$$\lambda_3 < \lambda < \lambda_4;$$

where, $\lambda_3, \lambda_4, \mu_2, \mu_4, k_A$ are defined as:

$$\lambda_3(k_1, \alpha, \mu_V) = \frac{1}{2}\left(\frac{2-\alpha(2+k_1(-2+\mu_V))}{(1+\alpha(-1+k_1))^2} - \sqrt{-\frac{\alpha^2 k_1^2 \mu_V(4+\alpha(-4+4k_1-\mu_V)+\mu_V)}{(-1+\alpha)(1+\alpha(-1+k_1))^4}}\right),$$
$$\lambda_4(\alpha, k_1, \mu_V) = \frac{1-\alpha-\alpha k_1 \mu_V}{(-1+\alpha)^2},$$
$$\mu_2(\alpha, k_1) = \frac{1-\alpha}{k_1},$$
$$\mu_4(\alpha, k_1) = \frac{1-\alpha}{\alpha k_1}$$
$$k_A(\alpha) = \frac{(2-\alpha)-\sqrt{3-2\alpha}}{1-\alpha}$$

Outside of the range where the FOC has a unique solution, τ_2^* is either 1 or α, which we determine based on whether $\partial C_2/\partial\tau$ is positive or negative. This algebra yields the following boundary solutions when $\alpha \le \tau \le 1$:

$$\tau_2^* = \begin{cases} \alpha, & \text{if} \quad \lambda < \lambda_3 \quad \text{since} \quad \partial C_2/\partial\tau \ge 0 \\ \alpha, & \text{if} \quad k_1 < k_A \text{ and } \mu_V < \mu_2, \quad \text{since} \quad \partial C_2/\partial\tau \ge 0 \\ 1, & \text{if} \quad \max\{2, \mu_3\} < \mu_V \text{ and } \max\{0, \lambda_4\} < \lambda < 1 \quad \text{since} \quad \partial C_2/\partial\tau \le 0 \end{cases} \tag{EC.7}$$

where, μ_3 and k_A are defined as:

$$\mu_3(\alpha, k_1) = \frac{1-\alpha}{k_1}$$
$$k_A(\alpha) = -\sqrt{\frac{3-2\alpha}{(-1+\alpha)^2}} + \frac{-2+\alpha}{-1+\alpha}.$$

Note that the region $\mu_2 < \mu_V < \mu_3$ and $\lambda > \lambda_4$ does not exist. Therefore, for the sake of simplicity we do not further break down the state space in the remainder of the proof.

With the optimal τ obtained when $0 < \tau < \alpha$ or $\alpha < \tau < 1$, we finally merge the regions to find τ^* for each combination of parameters.

We realize the following relationship:

$$0 < k_A < \frac{1}{2} < 1 - \alpha.$$

Note that when $k_1 < \frac{1}{2}$, $\tau_1^* = \alpha$ and C_1 is decreasing. Therefore, $\tau^* = \tau_2^*$ from Case 2.

When $k_1 \geq \frac{1}{2}$, we observe:

$$2 < \mu_2 < \mu_1 < \mu_4.$$

Note from Equation EC.5 that when $k_1 \geq \frac{1}{2}$ and $\mu_V > \mu_1$, $\tau_1^* = \alpha$ and C_1 is decreasing. Therefore, again, $\tau^* = \tau_2^*$ from Case 2.

However, when $k_1 \geq \frac{1}{2}$ and $\mu_V < \mu_1$, the solutions from Case 1 can be the overall solution to τ^*. Observe that the following relationship holds when $\mu_V < \mu_1$:

$$0 < \lambda_1 < \lambda_2 < \lambda_3 < \lambda_4$$

Further, note that when $\lambda_2 < \lambda$, $\tau_1^* = \alpha$ and C_1 is decreasing. Therefore, again, $\tau^* = \tau_2^*$ from Case 2. Also, note that when $\lambda < \lambda_3$, $\tau_2^* = \alpha$ and C_2 is increasing; therefore, $\tau^* = \tau_1^*$ in this case. Hence, overall, when $\lambda < \lambda_2$, $\tau^* = \tau_1^*$.

Table EC.1 summarizes the optimal threshold τ^* for all parameter combinations.

□

EC.1.1. *Proof of Proposition 1*

To prove Proposition 1 we must show that the area for which $\tau^* = \alpha$ is decreasing with k_1.

For this, it suffices to show that the μ_V and λ ranges in which $\tau^* = \alpha$ are both decreasing with k_1. Referring to Table EC.1, these ranges can be readily found. The following statement is true, and thus proves Proposition 1.

For all $0 < \alpha < \frac{1}{2}$, $0 < \lambda < 1$, $0 < k_1 < 1 - \alpha$, $\mu_V > 2$:

$$\begin{cases} \frac{\partial\left(\mu_4(k_1,\alpha) - \mu_2(k_1,\alpha)\right)}{\partial k_1} < 0 \\ \frac{\partial\left(\mu_4(k_1,\alpha) - \mu_1(k_1,\alpha)\right)}{\partial k_1} < 0 \\ \frac{\partial \lambda_3(k_1,\alpha,\mu_V)}{\partial k_1} < 0 \\ \frac{\partial\left(\lambda_3(k_1,\alpha,\mu_V) - \lambda_2(k_1,\alpha,\mu_V)\right)}{\partial k_1} < 0 \end{cases} \tag{EC.8}$$

□

k_1	μ_V	λ	τ^*
$k_1 < k_A$	$2 < \mu_V < \mu_2$	$0 < \lambda < 1$	α
	$\mu_2 < \mu_V < \mu_4$	$0 < \lambda < \lambda_3$	α
		$\lambda_3 < \lambda < \lambda_4$	τ_2
		$\lambda_4 < \lambda < 1$	1
	$\mu_4 < \mu_V$	$0 < \lambda < 1$	1
$k_A < k_1 < 1/2$	$2 < \mu_V < \mu_4$	$0 < \lambda < \lambda_3$	α
		$\lambda_3 < \lambda < \lambda_4$	τ_2
		$\lambda_4 < \lambda < 1$	1
	$\mu_4 < \mu_V$	$0 < \lambda < 1$	1
$1/2 < k_1 < 1-\alpha$	$2 < \mu_V < \mu_1$	$0 < \lambda < \lambda_1$	0
		$\lambda_1 < \lambda < \lambda_2$	τ_1
		$\lambda_2 < \lambda < \lambda_3$	α
		$\lambda_3 < \lambda < \lambda_4$	τ_2
		$\lambda_4 < \lambda < 1$	1
	$\mu_1 < \mu_V < \mu_4$	$0 < \lambda < \lambda_3$	α
		$\lambda_3 < \lambda < \lambda_4$	τ_2
		$\lambda_4 < \lambda < 1$	1
	$\mu_4 < \mu_V$	$0 < \lambda < 1$	1

Table EC.1 **Optimal threshold τ^* for all parameter combinations.**

Proof of Lemma 3

For each region in Table EC.1, note that when $\tau* = 0$ or $\tau* = \alpha$ or $\tau* = 1$, $\frac{\partial \tau^*}{\partial \mu_V} = 0$ and $\frac{\partial \tau^*}{\partial \lambda} = 0$. For regions where $\tau* = \tau_1$ or $\tau* = \tau_2$, it can also easily be shown that:

$$\begin{cases} \frac{\partial \tau_2}{\partial \mu_V} > 0 \\ \frac{\partial \tau_2}{\partial \lambda} > 0 \\ \frac{\partial \tau_1}{\partial \mu_V} > 0 \\ \frac{\partial \tau_1}{\partial \lambda} > 0 \end{cases}$$

Also recall that when $k_1 < 1/2$: $0 < \lambda_3 < lambda_4$ and $2 \leq \mu_2 < \mu_4$; and when $1/2 < k_1 < 1-\alpha$: $0 < \lambda_1 < \lambda_2 < \lambda_3 < lambda_4$ and $2 \leq \mu_1 < \mu_4$ so the regions where $\tau^* = 0 < \tau_1 < \alpha < \tau_2 < 1$ are also increasing in μ_V and λ.

□

Proof of Proposition 2

Proposition 2 can be readily inferred from Table EC.1. □

Proof of Proposition 3

Proposition 3 can be readily inferred from Table EC.1. □

Proof of Lemma 1

Denote the cumulative distribution functions (CDF) of departures from the VPP and direct arrivals to the ED (i.e., after triage) by $F_a(t)$ and $F_b(t)$, respectively. The probability of an arrival at time $T \leq t$ can be written as:

$$\begin{aligned}F_{a\cup b}(t) &= \Pr\{T \leq t\} = \Pr\{\text{departure from VPP} < t\} \cup \Pr\{\text{direct arrival} \leq t\}\\ &= F_a(t) + F_b(t) - F_a(t)F_b(t)\end{aligned}$$

The direct arrival interarrival time distribution is an exponential distribution with rate $(1-\tau)\lambda$. Hence,

$$F_b(t) = 1 - e^{-(1-\tau)\lambda t}$$

To find $F_a(t)$, we leverage the results from Tang (1994). Denote $\lambda_v = p(\tau)\tau\lambda$. We have:

$$\text{Vacation length CDF} = V(t) = 1 - e^{-t/u}$$

$$v(\lambda_v) = \int_0^{\infty} e^{-\lambda_v x} dV(x) = \frac{1}{1+\lambda_v u}$$

$$\widetilde{V}(t) = \frac{\int_0^{\infty} V(t+x)\lambda_v e^{-\lambda_v x}dx - v(\lambda_v)}{1-v(\lambda_v)} = 1 - e^{-t/u}$$

$$p_0 = \frac{(1-\lambda/\mu_V)\Big(1-v(\lambda_v)\Big)}{\lambda_v u}$$

$$F(t) = 1 - e^{-\lambda_v t}$$

$$G(t) = 1 - e^{-\mu_V t}$$

Finally, Equation 21 from Tang (1994) shows the interdeparture time CDF of the VPP in steady state:

$$F_a(t) = (1 - p_0)G(t) + p_0 \int_0^t dF(x) * dG(x) * d\widetilde{V}(t)$$

Finally, $f_a(t) = dF_{a\cup b}(t)/dt$.

□

Proof of Lemma 2

It can be shown that the functional form of the receiver operating characteristic (ROC) curve of Equation 4 is as follows:

$$TPR(FPR \mid k_1, \alpha) = \begin{cases} \dfrac{(1-\alpha-\alpha k_1)}{(1-\alpha)k_1} FPR, & \text{if } 0 \leq FPR < k_1 \\ \\ \dfrac{(1-\alpha-k_1)+\alpha k_1 FPR}{(1-\alpha)(1-k_1)}, & \text{Otherwise.} \end{cases} \tag{EC.9}$$

where, TPR and FPR are the true positive rate and false positive rate, respectively.

The AUC is calculated by integrating the ROC curve, which results in the following:

$$AUC = \int_0^1 TPR(FPR \mid k_1, \alpha) dFPR = 1 - \frac{k_1}{2(1-\alpha)} \tag{EC.10}$$

□

EC.2. Simulation of the ED Flow

To test the validity of the findings obtained from our simplified model (Section 5) and also to gain deeper insights, we developed a simulation model of the ED flow and calibrated it with hospital data. Section EC.2.1 describes the simulation model and steps taken in validating it. Section EC.2.2 showcases how to map the analytical model for the VPP presented in Sections 4-5 to a real-world ED and identify the resulting optimal routing policy. Section EC.2.3 highlights the differences between three distinct routing rules for the VPP. In Section EC.2.4, we conduct a sensitivity analysis to evaluate the impact of a physician self-assignment system on the LOS of the VPP-based ED. In Section 7 at the main body of the manuscript, we extend our simulation environment to (a) compare the VPP design with other ED flow approaches introduced in the Introduction (e.g., LOS and PIT) and (b) generate insights into when, and for which hospitals, the VPP design is advantageous.

EC.2.1. Data-Driven Simulation Model: Development and Validation

We develop a simulation model of the old Mayo Clinic ED based on the operational constraints of the system and the clinical characteristics of the population it serves. Our aim is to design a realistic virtual test bed of the ED, where we can test the impact of different routing and prioritization protocols on patients' average LOS and waiting time.

Arrival Process. We assume that the arrivals to the ED follow a non-stationary Poisson process with a dynamically changing rate during the day, following the empirical arrival rates of the ED presented in Figure 2. The arrival rate in our simulations is specified for each ESI class, ranging from one to five, and for each hour of the day.

Patient Population. Each simulated arrival is sampled from a synthetic pool of patients based on the ED records, using the synthetic data vault (SDV) framework (Patki et al. 2016). The SDV process involves three consecutive parts: (1) data extraction and processing (DataNavigator); (2) generative model development (Modeler); (3) synthetic data creation (Sampler). SDV first estimates the distribution of each individual feature and the covariance between all independent variables in the dataset. Subsequently, the algorithm selects between a set of common distributions, including the truncated Gaussian, the uniform, or the beta distribution, the one that best matches the real data according to the p-values of the Kolmogorov-Smirnov test. Thus, the shape of the chosen cumulative distribution function for each feature is determined by the significance level of the statistical test. Finally, a Gaussian Copula function is applied to characterize the joint distribution of all derived random variables, ensuring that the shape of different distributions does not influence the covariance estimates. The SDV approach allows us to generate a realistic synthetic patient population that approximates the patient volume and mix that is served for each hour of the day at our partner hospital.

Simulating Assignments to VPP and ED (Current Practice). In the current practice, all arriving patients are assigned to a physician using a randomized round-robin algorithm. This assumption is relaxed in Section EC.2.4 where we explore the implications of a physician self-assignment system. Patients are also triaged and then sent to the waiting area. By default, patients waiting will be taken to an ED bed and served by their assigned physician. However, when a physician becomes available, she considers the pool of patients assigned to her who are still in the waiting area and assesses whether they can be served in the VPP. If the physician decides that a patient can be served in the VPP, the physician requests that the patient be moved to the VPP. We model this ad-hoc selection as a Bernoulli process, where the probability of success (i.e., selection to the VPP) is a function of each patient's ESI level and hour of the day. We observe that this Bernoulli process matches our data relatively well (see Table EC.2). It also ensures that patients are served in the VPP (in the simulated environment) only during the hours in which the VPP is open. Upon completion of the VPP visit, depending on the value of the test results, patients may either (a) be sent to the main ED queue for additional ED care, or (b) get discharged to go home directly from the VPP. The overall patient flow is based on Figure 1c.

Our simulation analyses extend the analytical framework presented earlier to consider a system that involves multiple physicians. We leverage the overall patient arrival rate to the ED and the average number of physicians working at any given hour from our data. Our approach considers the "competition" among physicians for utilizing the VPP, rendering it a shared resource in the ED.

Service Process. Once a patient has been seen in the VPP, tests are ordered. We assume that VPP patients will have to wait for their tests to be completed to determine whether they need to be served in the main ED. We extract disposition times and test times from our data and observe that for about half of the ED visits (49.5% for Main ED patients and 53.7% for VPP patients), a test has been ordered prior to the physician's first contact (see Fig. EC.8). Hence, we assume that a patient's service time begins from the earlier of

Hour of the Day	ESI=1	ESI=2	ESI=3	ESI=4	ESI=5
0	0.00%	0.00%	0.00%	0.78%	0.00%
1	0.00%	0.50%	0.00%	0.00%	0.00%
2	0.00%	0.00%	0.00%	0.00%	0.00%
3	0.00%	0.00%	0.00%	0.00%	0.00%
4	0.00%	0.00%	0.00%	0.00%	
5	0.00%	0.00%	0.00%	0.00%	0.00%
6	0.00%	0.00%	0.00%	0.00%	0.00%
7	0.00%	0.00%	0.00%	0.00%	0.00%
8	0.00%	0.00%	0.31%	0.97%	0.00%
9	0.00%	0.11%	1.01%	2.40%	13.33%
10	0.00%	2.09%	4.95%	10.41%	15.79%
11	0.00%	4.46%	12.14%	21.05%	26.09%
12	0.00%	5.16%	17.20%	24.59%	68.75%
13	0.00%	5.00%	16.17%	28.57%	33.33%
14	0.00%	5.83%	15.05%	24.07%	31.25%
15	0.00%	3.86%	13.82%	20.06%	30.00%
16	0.00%	5.70%	11.92%	17.88%	40.00%
17	0.00%	3.98%	11.00%	13.83%	10.53%
18	0.00%	1.68%	6.64%	9.60%	18.18%
19	0.00%	1.54%	2.07%	6.19%	16.67%
20	0.00%	0.94%	1.05%	1.48%	4.55%
21	0.00%	0.20%	0.69%	1.15%	6.25%
22	0.00%	0.00%	0.39%	0.51%	0.00%
23	0.00%	0.33%	0.00%	0.00%	0.00%

Table EC.2 Proportion of patients served in the VPP of the old Mayo ED during the study period for each ESI level.

first physician contact and first ordered test, and ends when a patient is either admitted to the hospital or discharged to go home. Also, we observe that for about 10% of patient visits, a test result becomes ready after the disposition decision is made. Since these have a low percentage of occurrence, we exclude them from the service duration and do not assume they cause further delays once the disposition decision has been made. Since ED service includes both treatment and testing, we also incorporate, as system parameters, the average testing and treatment durations separately for each ESI level and hour of the day. We assume that these durations follow time-varying exponential distributions, with means extracted from our data.

In addition, we model the probability that a patient is admitted to an inpatient unit after ED service based on ESI levels, and calibrate it using our data. Patients admitted to an inpatient unit after ED service often experience a "boarding time," which involves waiting in the ED until an inpatient bed becomes available. We model this using a log-normal distribution (see, e.g., Saghafian et al. (2023)) with means and standard deviations as functions of ESI and the hour of the day (obtained from our data).

	LOS			Wait		
Group	**Baseline**	**Simulation**	**p-value**	**Baseline**	**Simulation**	**p-value**
All	238	238	0.583	36	36	0.748
ESI=1	192	183	0.139	11	12	0.16
ESI=2	276	274	0.221	24	25	0.155
ESI=3	237	239	0.161	42	41	0.254
ESI=4	153	153	0.748	42	42	0.788
ESI=5	87	85	0.759	37	37	0.888

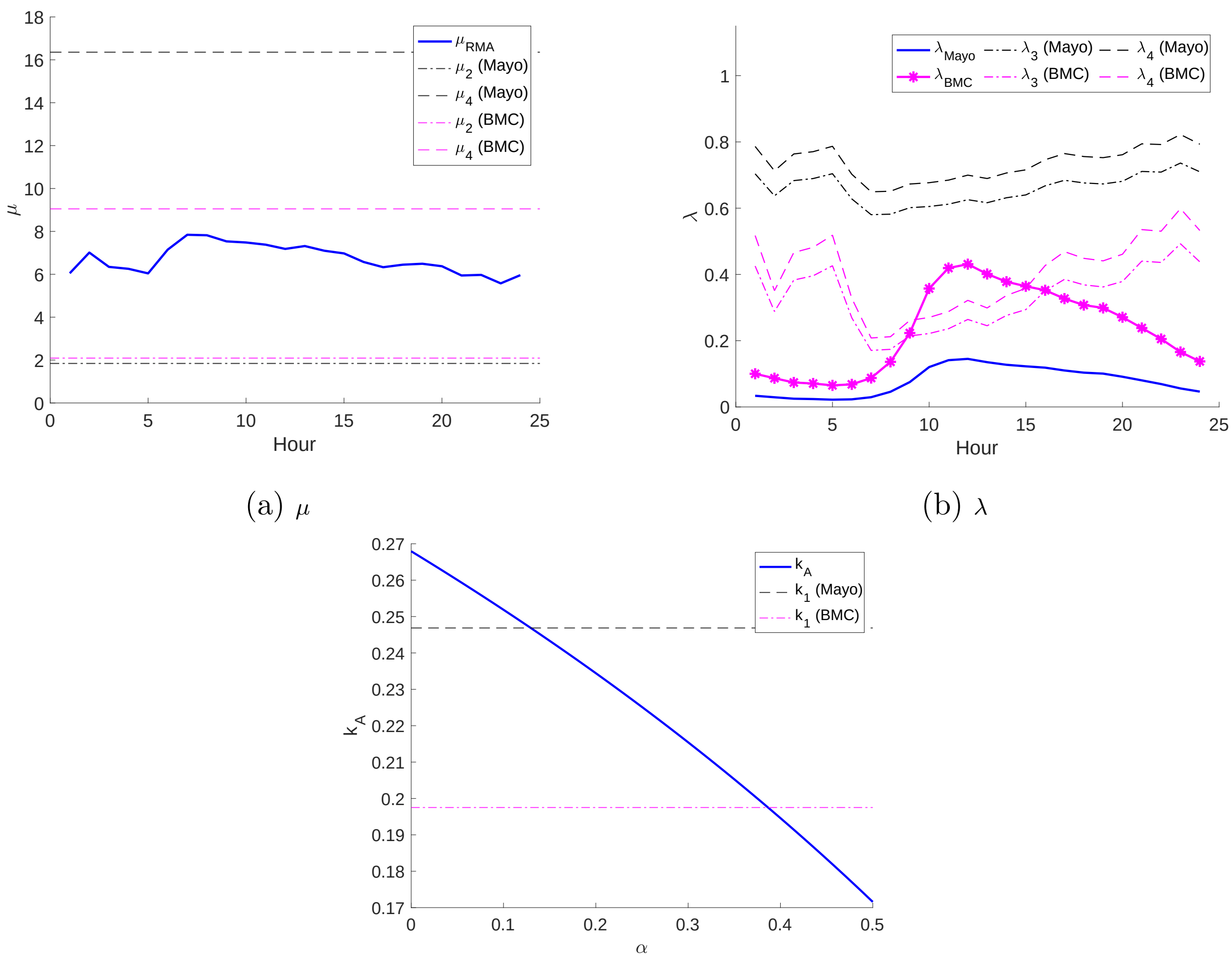
Table EC.3 Comparison of average LOS and waiting time (minutes) between the simulated and baseline values.

Validation. To validate our simulation model and ensure that it provides a realistic benchmark to the baseline (i.e., observed values from the current practice) at the Mayo Clinic, we perform a series of comparisons by making use of two well-defined metrics of operational performance. Specifically, we focus on average waiting time and LOS and calculate them both for the overall population and for each ESI level. We run the simulation for ten years and discard the first three years as a transient period. We compute the hypothesis test statistic for the two metrics of interest, comparing whether the baseline observed from our data has a different distribution compared to what we obtain from our simulation. As shown in Table EC.3, all p-values for the differences are large (> 0.5), indicating that the simulated system accurately approximates the current practice of the Mayo Clinic. This can also be seen by noting that the difference between the baseline and simulation in terms of both the overall average LOS and waiting time metrics is less than a minute. Hence, our simulation environment provides a realistic test bed to evaluate the impact of our proposed VPP design compared to both the current VPP design and alternative ED patient flow approaches (e.g., FT and PIT) discussed earlier.

EC.2.2. Mapping the Analytical Model to Real-World Healthcare Systems

To identify the optimal VPP design for the old ED of our partner hospital using our analytical model (Section 4), we need to specify the values of $\alpha, k_1, \mu_V, \lambda$ (see Table EC.1).

The old ED at Mayo Clinic Arizona. To compute α, we use the dependent variable of the proposed ML model (Section 6.2). Specifically, we note that the care of the 9,796 patients out of the 49,350 did require an ED bed, and thus, we set our baseline α to 19.85%. Using this value, we next leverage Equation (6), which indicates that $k_1 = 0.2469$. As shown in Figure EC.1c, at the Mayo Clinic we are at the regime where $k_A < k_1$. We next determine μ_V, which reflects the relative speed of the VPP compared to the main ED. By design, physicians who serve patients in the VPP strive to complete the consultation within 20 minutes. Assuming this time constraint on average, we can focus only on the average service rate of the main ED per hour of the day and make use of it to obtain the ratio between μ_V and μ_E. Our analysis shows that, at our partner hospital, the service rate of the VPP is six to eight times that of the main ED. Thus, on average, the service duration in the main ED is between 120 minutes and 160 minutes, depending on the hour of the day (see Figure EC.1a). From Proposition 2, we next compute the values of μ_2 and μ_4, verifying that $\mu_2 < \mu_V < \mu_4$. Following Table 1, we observe that our partner hospital falls in the policy regime where $\tau^* = \alpha$ for all $0 < \lambda < \lambda_3$ (Figure EC.1b). Figure EC.1 illustrates the sensitivity analysis on the system parameters to ensure that the proposed policy is robust to data perturbations and hourly changes during the day.



(a) μ

(b) λ

(c) k_1

Figure EC.1 Sensitivity analysis of the Mayo Clinic ED system parameters.

The ED at the Boston Medical Center (BMC). We also repeat our analysis for BMC, using their data to create yet another benchmark and show how the optimal VPP routing policy depends on the hospital characteristics. BMC primarily serves a higher portion of underprivileged population compared to the Mayo ED with greater racial diversity (Bertsimas et al. 2020b). In addition, the proportion of patients that require an ED bed is low due to the high prevalence of low acuity cases. Leveraging the findings of Feizi et al. (2023), we approximate BMC's α by scaling Mayo's α by the ratio of ESI-4 and ESI-5 patients served in BMC to that of Mayo clinic. We also approximate the hourly arrival rates by scaling up Mayo's hourly arrival rate by the ratio of annual patient volume at BMC to that of Mayo (Mackenzie Bean 2023). We further assume that the trained ML model achieves the same performance as the one presented in Section 6.3. As shown in Figure EC.1c, we are in the regime where $k_A > k_1$. Moreover, if we hypothesize that BMC was able to provide an equivalent amount of resources (rooms and physicians) to achieve the same μ_V as the Mayo ED, then $\mu_2 < \mu_V < \mu_4$ would still apply. However, the average arrival rate λ_{BMC}, changes the optimal regime throughout the day. Specifically, as illustrated in Figure EC.1b, $0 < \lambda < \lambda_3$ between 4.00 pm and 9.00 am ($\tau^* = \alpha$); $\lambda_3 < \lambda < \lambda_4$ between 9.00 am and 9.30 am as well as between 3.00 pm and 4.00 pm. ($\tau^* = \tau_2$); $\lambda_4 < \lambda$ during the hours of 9.30am and 3.00pm ($\tau^* = 1$). This setting highlights the potential variability of the optimal policy throughout the day. In practice, the ED administrators of the BMC, could approximate the optimal design by implementing $\tau^* = \alpha$ during the hours of low demand and increasing it to $\tau^* = 1$ throughout the morning and afternoon hours, leveraging the VPP as a screening tool for any patient in the ED.

EC.2.3. Combined Routing and Patient Prioritization

Our analyses in the previous section shed light on the best policies that should be followed in practice for routing patients to the VPP. However, among patients that are routed to the VPP, an ED can follow various prioritization mechanisms. Augmenting patient routing policies with prioritization rules might yield significant benefits in practice. To gain insights into suitable rules that allow for both routing and prioritization, we consider three implementable policies and compare them with the current practice at the Mayo Clinic. Specifically, we consider the following policies:

- **Baseline**: This scenario simulates the current practice at the Mayo Clinic. The implementation of the VPP operation is guided by the empirical data as described in Section EC.2.1.

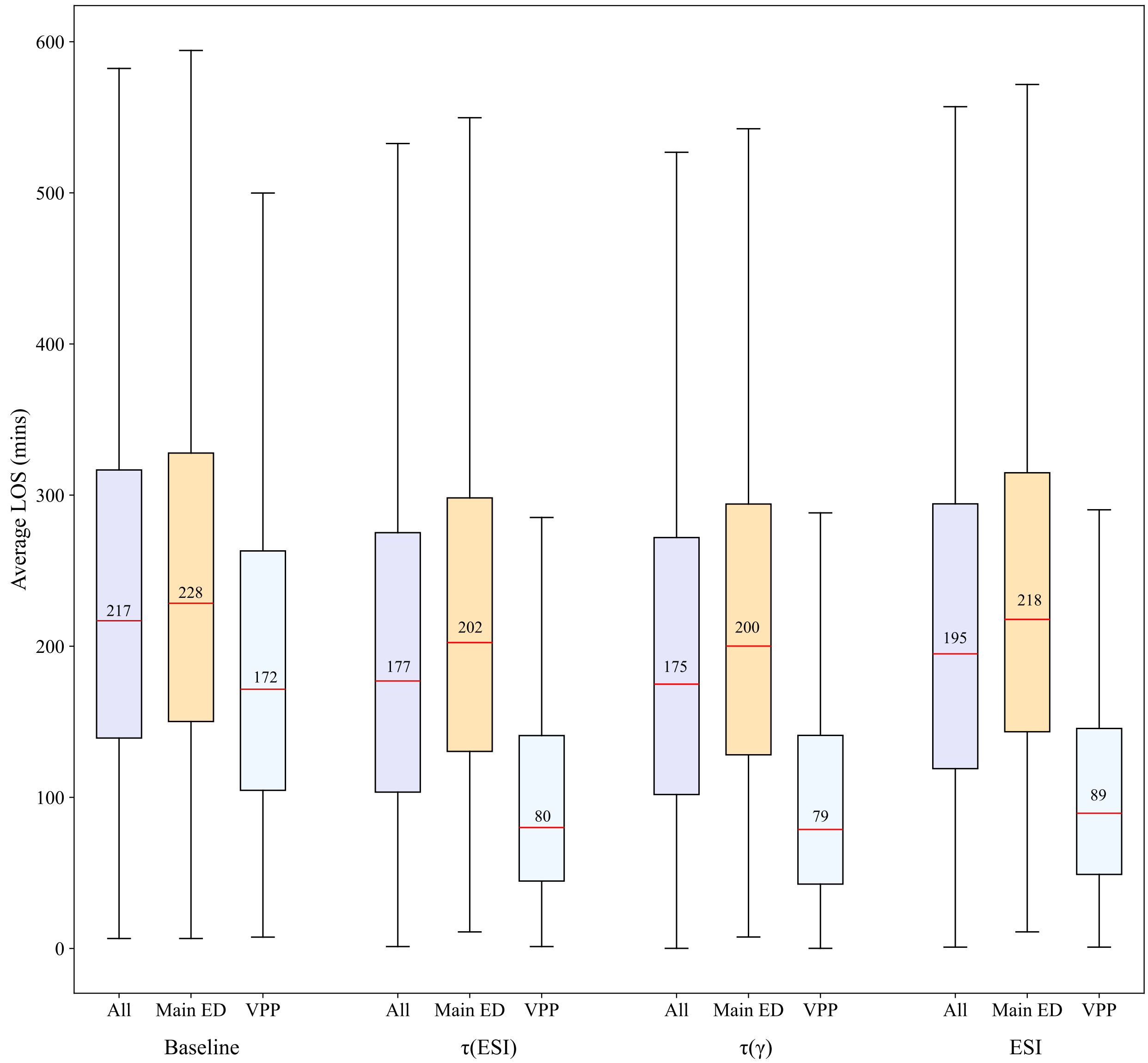


Figure EC.2 **Average LOS of all patients, patients served in the main ED, and patients served in the VPP at the old Mayo Clinic ED.**

- $\boldsymbol{\tau}^*$(**ESI**): Following the design presented in Figure 3, under this policy, all patients with $\hat{\gamma} < \tau^*$ are routed to the VPP, where $\hat{\gamma}$ is obtained from the ML model. Furthermore, among patients with $\hat{\gamma} < \tau^*$, priority is given to patients with a lower ESI level. That is, patients are (a) routed to the VPP based on the ML model's score and (b) prioritized there based on their ESI level.
- $\boldsymbol{\tau}^*(\hat{\boldsymbol{\gamma}})$: Similar to the previous policy, patients with $\hat{\gamma} < \tau^*$ are routed to the VPP. However, instead of ESI, prioritization is done based on the predicted score, $\hat{\gamma}$. That

is, both routing and priority decisions for utilizing the VPP are based on the ML model's output.

- **ESI**: Under this policy, both routing and priority decisions are based on the ESI level. In particular, all patients with ESI>3 (i.e., low acuity patients) are routed to the VPP. Under this policy, we assume that the ML model is not implemented, and instead, a strict rule based on ESI is used (similar to how EDs make use of their FT units).

Figure EC.2 shows that all of the three policies considered ($\boldsymbol{\tau}^*(\textbf{ESI})$, $\boldsymbol{\tau}^*(\hat{\gamma})$, **ESI**) lead to substantial improvements in the overall system's performance compared to current practice. This is to some extent expected, given that in the current practice at our partner hospital VPP routing and priority decisions are made in an ad-hoc manner by individual physicians. Furthermore, we observe that the $\boldsymbol{\tau}^*(\hat{\gamma})$ policy results in an average LOS of 177 minutes, which corresponds to a 18.4% reduction compared to the current practice. We observe small differences between $\boldsymbol{\tau}^*(\hat{\gamma})$ and $\boldsymbol{\tau}^*(\textbf{ESI})$. This is mainly because ESI is the primary driver of risk for $\hat{\gamma}$ (see the SHAP graph in Figure EC.7). Hence, there are only minor differences between these two prioritization policies. However, we observe that both of these lead to significant benefits compared to the **ESI** policy, highlighting that using the ML model and following a data-driven VPP design is superior to an ESI-based rule that blindly sends the low acuity (ESI>3) patients to the VPP. Similar findings are uncovered when we focus on the average waiting time in the system.

Put together, these results indicate that our partner hospital should change the current practice of routing patients to the VPP. In particular, we find that making use of the ML model to obtain predicted risk scores and following the $\boldsymbol{\tau}^*(\hat{\gamma})$ policy can go a long way. The results of our analysis for the BMC ED are summarized in Figure EC.3. The simulation leads to a similar conclusion, suggesting that the $\boldsymbol{\tau}^*(\hat{\gamma})$ policy yields the greatest overall reduction of LOS in the system.

EC.2.4. Patient Assignment System Sensitivity Analysis

In this section, we relax the hypothesis that the ED uses a rotational patient assignment system to compare the impact of the VPP design in an ED with physician self-assignment. This setting allows us to evaluate the system's performance when physicians are tasked with choosing which patients to treat, rather than relying on an automated round-robin assignment system.

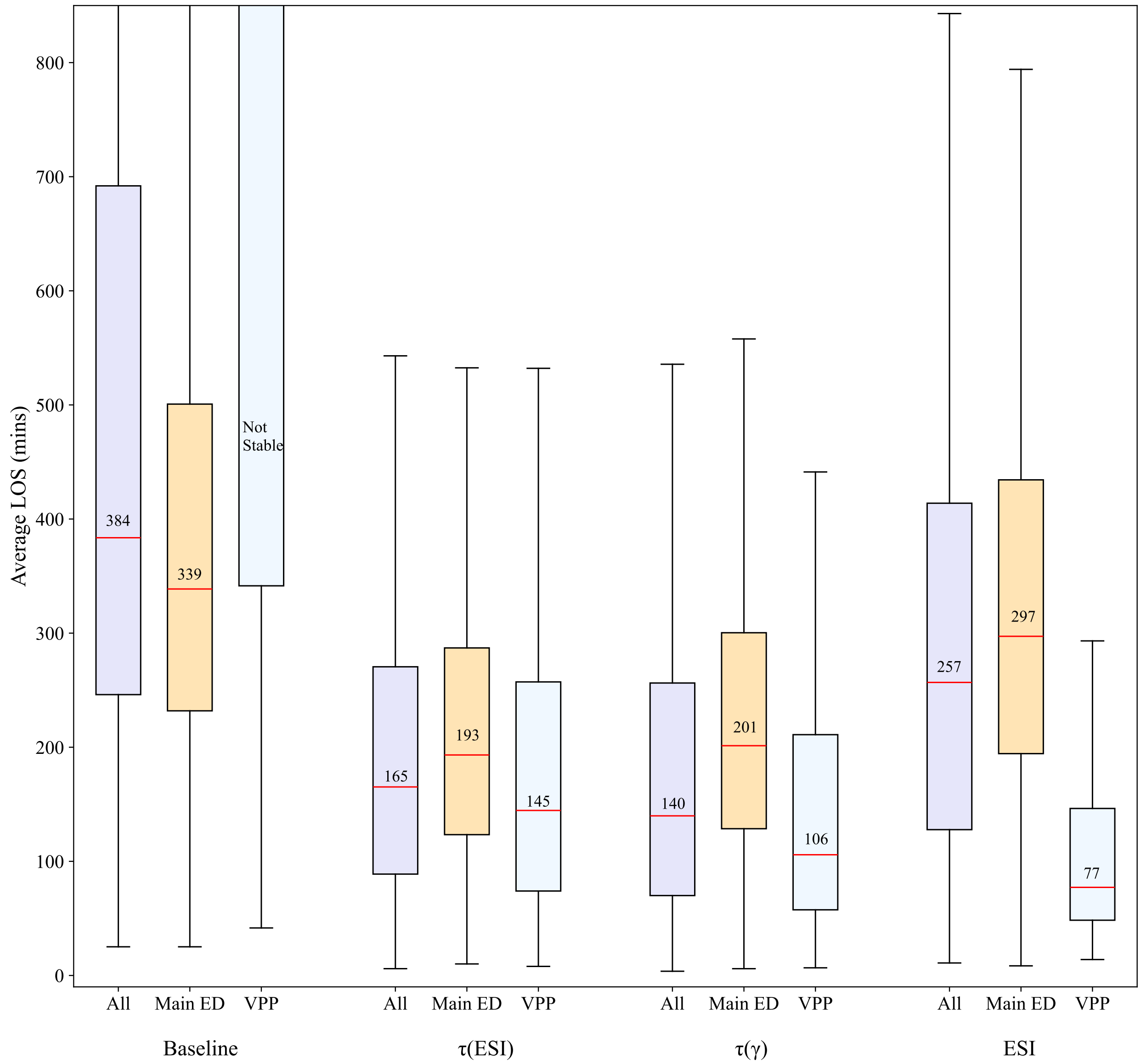


Figure EC.3 Average LOS of all patients, patients served in the main ED and patients served in the VPP at the BMC ED.

Modeling a self-assignment system in an ED simulation requires capturing the complex decision-making processes of physicians and their interactions with the ED environment. The key challenge lies in accurately representing the heuristics that physicians use to select patients and how these decisions impact the overall efficiency and effectiveness of the ED. In the absence of data from such a system, we assumed the following process for self-assessment: Following the approach presented in (Traub et al. 2016b) and leveraging productivity estimates for ED physicians from the literature (Joseph et al. 2018), we assume that each physician begins their shift with a random allocation of up to three patients in their queue depending on the number of patients waiting at the ED. After starting their shift, physicians are subsequently tasked with choosing a new patient to treat as soon as the treatment of one of their existing patients is marked as completed. Patients are then ranked by each physician first based on ESI and subsequently based on waiting time. Thus, we assume that physicians will first prioritize a patient of higher acuity (lower ESI), in line with the ED general prioritization rules, and then choose within the ESI category the patient with the longest waiting time.

We apply the self-assignment rule in the $\tau^*(\hat{\gamma})$ version of the old Mayo ED system (see Section EC.2.3 for a description). In accordance with the literature (Traub et al. 2016b, Hirshon et al. 1996), our sensitivity analysis reveals higher variation in the expected ED performance when patient assignment is driven by physicians rather than a rotational algorithm. However, we do not identify substantial differences in the average LOS for all patients in the ED between the two patient assignment approaches, as the average LOS ranges between 172 and 178 minutes for the self-assignment policy across different randomized runs of the simulation. These results provide evidence that under both patient assignment approaches the proposed VPP design can lead to considerable improvements in patient LOS compared to the baseline.

We would like to acknowledge that there might be multiple alternative designs of a self-assessment patient assignment process. For example, the presented approach does not assume any strategic or heterogeneous physician behavior. Nevertheless, these findings provide supporting evidence regarding the generalizability of the proposed queueing model beyond an ED with a rotational patient assignment algorithm. To further verify the benefit of the VPP design, additional retrospective and prospective studies are needed in EDs with an active physician self-assignment protocol.

EC.3. Simulated Design for the FT and PIT Systems

We design the FT and PIT based on Feizi et al. (2023) and Franklin et al. (2021), respectively, which employ these policies in their study settings. Below we provide details on the implementation of the FT and PIT policies:

- **Fast-Track (FT)**: All patients with ESI>3 are routed to dedicated beds in the FT section of the department while only patients with ESI≤ 3 use the resources available in the main ED. We assume that at any hour, the FT is staffed with half as many physicians in the main ED and that one patient at a time can be served by an FT worker.
- **Physician-In-Triage (PIT)**: All patients are first seen by a physician during the triage stage, and only patients who require ED care will be sent to the queue. Triage physicians may also initiate the tests. In implementing the PIT policy, we assume that there are always two physicians at the triage stage and that the examination time of a physician is similar to that of an VPP. However, the main ED will operate with two fewer physicians during the hours in which it was originally staffed with over two physicians.

Our analysis attempts to match all three patient streaming systems in terms of the number of resources (i.e., the total number of beds and physicians) throughout a simulated day. Thus, it is possible, under specific conditions, to study scenarios under which at least one of the approaches leads to an unstable system (see Table 3). Note that inevitably we must have two beds working simultaneously and additional physicians in simulating the FT since, by design, it must operate with two separate sections (FT and main ED). To perform a realistic comparison across the VPP, FT, and PIT approaches, we leverage the synthetically generated data from the Mayo Clinic.

EC.4. VPP Utility: Age Sensitivity Analysis

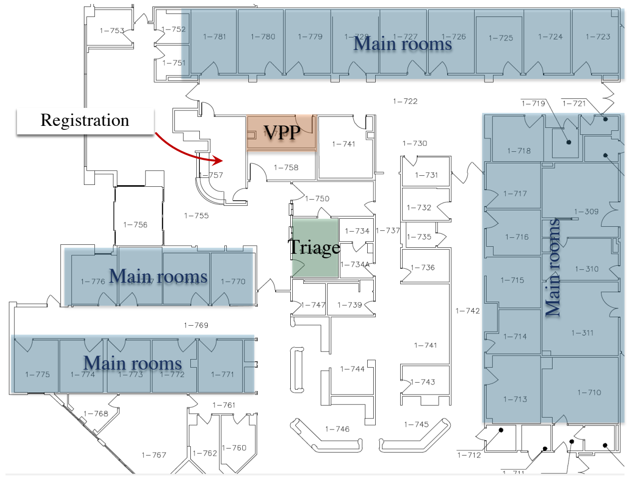
Building on the sensitivity analysis on the distribution of the patient population's level of acuity, we extend our results to the patient age. To this end, we conduct a series of simulations in which we alter the age distribution such that the average patient age lies in the set $\{40, 50, 60, 70\}$.

Population	Mean Age	FT	PIT	VPP
All	40	263.3 (262.2, 264.4)	456.7 (453.1, 460.3)	190.2* (189.3,191.0)
	50	253.1 (252.1, 254.1)	536.9 (532.0, 541.9)	192.6* (191.7,193.5)
	60	247.4 (246.5, 248.3)	616.8 (610.4, 623.2)	196.0* (195.1,196.9)
	70	243.1 (242.2, 244.0)	1092.7 (1072.5, 1112.8)	198.2* (197.3,199.0)
	Mayo ED	232.9 (232.1, 233.8)	785.1 (773.8, 796.4)	203.0* (202.2, 203.8)
Main ED	40	239.4 (238.4, 240.3)	509.2 (505.1, 513.2)	224.5* (223.5,225.6)
	50	241.1 (240.1, 242.0)	599.4 (593.8, 605.1)	226.3* (225.2,227.3)
	60	243.1 (242.2, 244.1)	687.2 (680.0, 694.4)	227.8* (226.8,228.8)
	70	244.2 (243.3, 245.2)	1223.9 (1201.1, 1246.7)	229.5* (228.4, 230.5)
	Mayo ED	245.6 (244.7, 246.6)	861.4 (848.8, 873.9)	229.1* (228.1, 230.0)
FT/VPP	40	332.6 (329.6, 335.7)	115.6 (114.5, 116.8)	110.7* (109.6,111.9)
	50	290.1 (287.4, 292.8)	115.8 (114.6, 117.0)	110.1* (108.9,111.2)
	60	261.5 (259.2, 263.9)	115.8 (114.6, 117.1)	111.6* (110.4,112.8)
	70	239.1 (237.0, 241.2)	117.6 (116.4, 118.9)	112.4* (111.2, 113.5)
	Mayo ED	173.5 (171.9, 175.2)	124.2 (122.8, 125.7)	111.2* (110.8, 111.6)

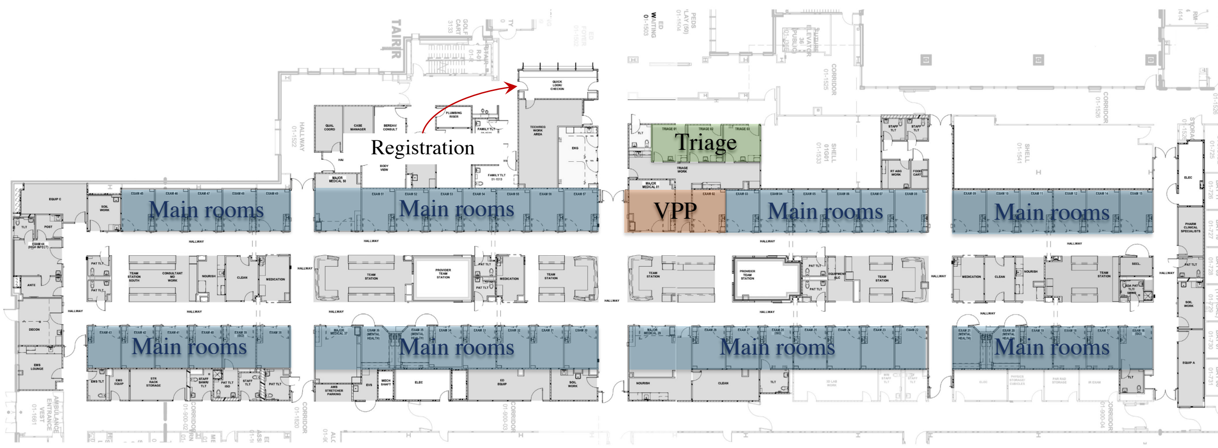
Table EC.4 Average LOS and 95% confidence intervals (indicated in parentheses) per patient subgroup across different ED flow designs. Four synthetic patient populations with a varying mean age at admission are considered in addition to the Mayo Clinic baseline sample. We indicate with an asterisk the best performing system for each population subgroup.

Table EC.4 illustrates that, given a certain set of resources, the age distribution does not impact the ranking of the three design approaches considered. Of note, the average LOS of all patients in the system increases (decreases) when the distribution shifts to older populations in the case of the VPP and PIT (FT). The opposite trend in the FT is driven by the system behavior outside of the main ED. The average LOS of patients served in the FT significantly decreases for older populations, contrary to the case of PIT and VPP where the performance does not significantly change due to age variations. When focusing on the main ED patients, we observe that the LOS measure under PIT significantly increases for older populations. In the case of FT and VPP, we still observe an increase in the average LOS but with a smaller variation. These results highlight that the adaptability of the optimal VPP design leads to lower variations in the system's LOS as the population characteristics change.

EC.5. Additional Figures and Tables



(a) Old Mayo Clinic Arizona ED.



(b) New Mayo Clinic Arizona ED.

Figure EC.4 Physical room layout.

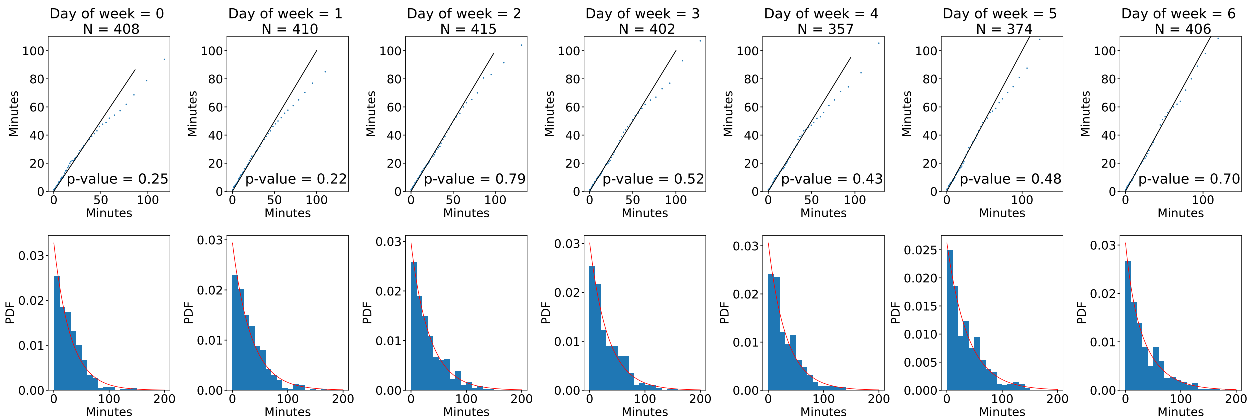


Figure EC.5 Matching interarrival time distribution of main ED with Equation 2.

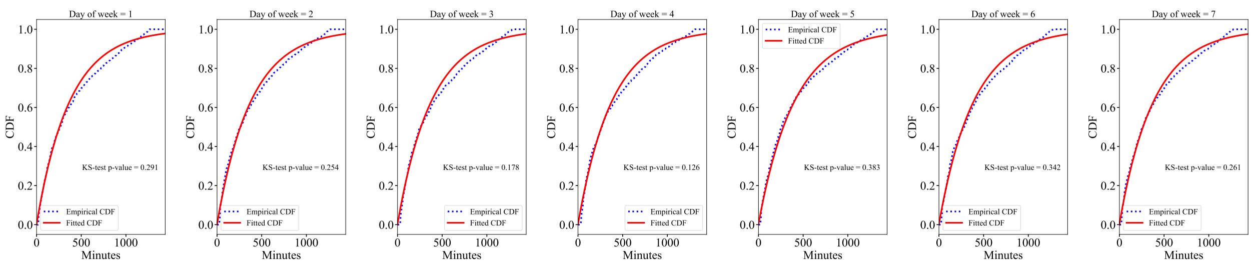


Figure EC.6 Matching the analytical and empirical CDF of arrival times to the main ED.

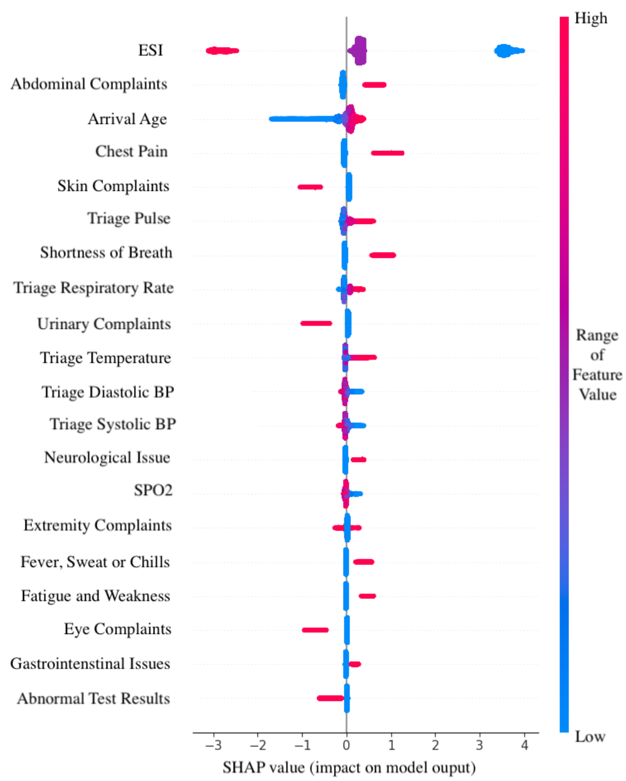


Figure EC.7 SHAP Plot for random forest models summarizing the contribution to risk prediction of the 20 most important features.

Independent Variable	Type	Distribution Information	% Missing
Demographic Information			
Arrival Age	Numeric	61.0 (43.0-74.0)	0.00%
Race White	Binary	43672.0 (88.5%)	0.00%
Race Asian	Binary	1407.0 (2.9%)	0.00%
Race Black or African American	Binary	2037.0 (4.1%)	0.00%
Race Choose Not to Disclose	Binary	518.0 (1.0%)	0.00%
Race Other	Binary	1687.0 (3.4%)	0.00%
Gender Male	Binary	22950.0 (46.5%)	0.00%
Acuity Score and Vitals at Triage			
ESI	Numeric	3.0 (2.0-3.0)	0.10%
SPO2	Numeric	98.0 (96.0-99.0)	0.30%
Diastolic Blood Pressure at Triage	Numeric	80.0 (72.0-89.0)	0.60%
Pulse Rate at Triage	Numeric	83.0 (72.0-96.0)	0.50%
Respiratory Rate at Triage	Numeric	18.0 (16.0-20.0)	0.50%
Systolic Blood Pressure at Triage	Numeric	136.0 (121.0-153.0)	0.60%
Temperature at Triage	Numeric	36.7 (36.5-36.9)	2.40%
Chief Complaint Categories			
Abdominal Complaints	Binary	6456.0 (13.1%)	0.00%
Abnormal Test Results	Binary	1829.0 (3.7%)	0.00%
Allergic Reaction	Binary	262.0 (0.5%)	0.00%
Back or Flank Pain	Binary	2642.0 (5.4%)	0.00%
Breast Complaints	Binary	61.0 (0.1%)	0.00%
Cardiac Arrhythmias	Binary	1055.0 (2.1%)	0.00%
Chest Pain	Binary	3679.0 (7.5%)	0.00%
Dizziness/Lightheadedness/Syncope	Binary	1969.0 (4.0%)	0.00%
Ear Complaints	Binary	254.0 (0.5%)	0.00%
Epistaxis	Binary	260.0 (0.5%)	0.00%
Exposures, Bites, and Envenomations	Binary	261.0 (0.5%)	0.00%
Extremity Complaints	Binary	5389.0 (10.9%)	0.00%
Eye Complaints	Binary	730.0 (1.5%)	0.00%
Falls, Assaults, and Trauma	Binary	2399.0 (4.9%)	0.00%
Fatigue and Weakness	Binary	1548.0 (3.1%)	0.00%
Fevers, Sweats or Chills	Binary	1908.0 (3.9%)	0.00%
Gastrointestinal Issues	Binary	3359.0 (6.8%)	0.00%
Genital Complaints	Binary	683.0 (1.4%)	0.00%
Medical Device or Treatment Issue	Binary	481.0 (1.0%)	0.00%
Medication Request	Binary	76.0 (0.2%)	0.00%
Neurological Issue	Binary	3457.0 (7.0%)	0.00%
Other	Binary	808.0 (1.6%)	0.00%
Other Pain	Binary	794.0 (1.6%)	0.00%
Psychiatric Complaints	Binary	206.0 (0.4%)	0.00%
Shortness of Breath	Binary	3050.0 (6.2%)	0.00%
Skin Complaints	Binary	2347.0 (4.8%)	0.00%
Upper Respiratory Symptoms	Binary	1941.0 (3.9%)	0.00%
Urinary Complaints	Binary	1446.0 (2.9%)	0.00%

Table EC.5 Summary statistics of all patient characteristics for the population sample from the old Mayo Clinic Arizona ED. For continuous variables, we report the average and the 95% confidence interval. In the case of binary variables, the table shows the count of observations where the feature is present and in parentheses the percent over the entire population. The last column includes the percent of missing values in the dataset for each independent variable.

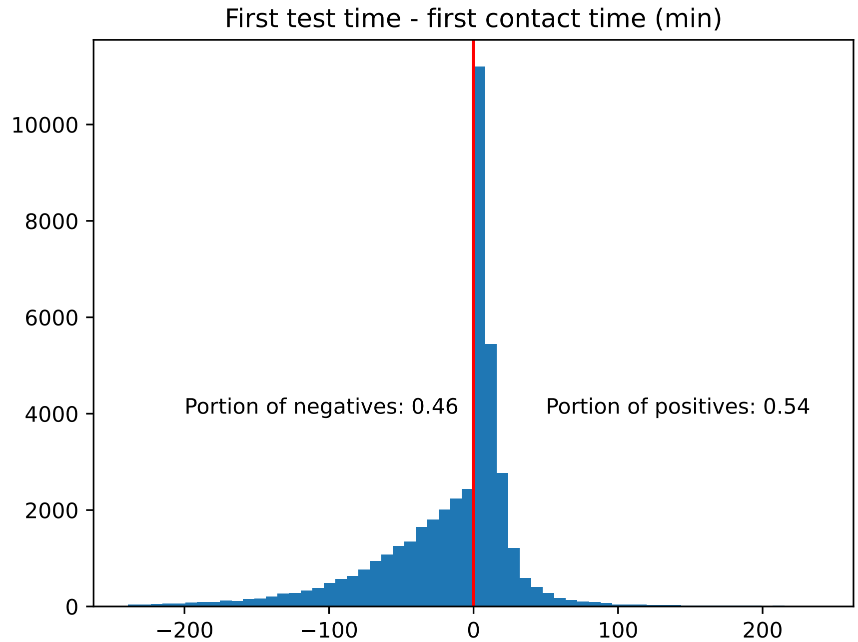


Figure EC.8 Time from first contact to first test. Negative values indicate that test was ordered prior to contact with physician.

	ESI 1	ESI 2	ESI 3	ESI 4	ESI 5
Strict FIFO Compliance (%)	98.22	78.22	67.59	88.68	97.60
Relaxed FIFO Compliance (%)	99.80	95.84	91.25	98.26	100.00

Table EC.6 Empirical validation summary of the FIFO assumption for the patient service order using the retrospective dataset from the old Mayo Clinic ED.

Note: This analysis aims to validate the First-In-First-Out (FIFO) assumption in the order patients receive care within each physician's queue based on the time of arrival. The analysis is conducted separately for each ESI category and focuses on the order in which physicians initiate their patients' treatment. The first two rows reflect the percentage compliance averaged across all physicians, weighted by the number of patients treated by each physician. Strict FIFO compliance indicates that the FIFO order based on the time of arrival was strictly adhered to in the order of care. Relaxed FIFO Compliance allows for permutations of up to one patient, meaning the physician could switch the order of only one patient. Based on these findings, the high percentages of both strict and relaxed FIFO compliance across all ESI levels indicate that the FIFO principle is generally adhered to in practice within each physician's queue.

Algorithm	Mean AUC	Std. of AUC
CART	0.8442	0.0024
Regularized logistic regression	0.8220	0.0051
Random forest	0.8458	0.0025
XGBoost	0.8446	0.0028
MLP	0.8451	0.0023
SVM	0.8324	0.0015

Table EC.7 Mean and standard deviation of the AUC metric on the testing set across all ML algorithms considered. The reported numbers correspond to the average performance on five random splits of the data.

Capacity	**Conditions**
Normal Operations	1. Patients in the waiting room for <20 minutes. 2. Number of patients in the ED is less than available ED beds.
Minor Overcapacity	1. Waiting room time 21-90 minutes OR; 2. Waiting room with 10 patients OR; 3. Number of ED patients exceed available ED beds by 10 (e.g., admitted patients waiting for a bed assignment) OR; 4. Team leader discretion.
Major Overcapacity	1. Waiting room time >90 minutes OR; 2. Waiting room with >20 patients OR; 3. More than 40 new patient arrivals in 2 hours OR; 4. Number of ED patients exceed available ED beds by 20 (e.g., admitted patients waiting for a bed assignment) OR; 5. Team leader discretion.

Table EC.8 Internal guidelines for activation of overcapacity and saturation plans for the new Mayo Clinic Arizona ED.

Chief Complaint	**Pre-Trial (N = 5,522)**	**Trial (N = 5,493)**	**p-value**
Cardiac Arrhythmias	2.41%	2.42%	p>0.05
Falls, Motor Vehicle Crashes, Assaults, and Trauma	5.36%	5.21%	p>0.05
Extremity Complaints	9.60%	9.90%	p>0.05
Shortness of Breath	6.50%	6.01%	p>0.05
Other	0.72%	0.67%	p>0.05
Abdominal Complaints	12.51%	13.18%	p>0.05
Abnormal Test Results	4.78%	5.10%	p>0.05
Chest Pain	7.61%	7.41%	p>0.05
Neurological Issue	6.52%	6.41%	p>0.05
Fevers, Sweats or Chills	2.75%	2.71%	p>0.05
Skin Complaints	4.40%	4.77%	p>0.05
Urinary Complaints	2.77%	2.89%	p>0.05
Genital Complaints	1.65%	1.46%	p>0.05
Foreign Body	0.16%	0.11%	p>0.05
Upper Respiratory Symptoms	4.98%	3.95%	p<0.01
Dizziness, Lightheadedness, and Syncope	3.48%	3.93%	p>0.05
Fatigue and Weakness	2.79%	3.02%	p>0.05
Allergic Reaction	0.62%	0.40%	p<0.05
Eye Complaints	1.47%	1.57%	p>0.05
Epistaxis	0.43%	0.62%	p>0.05
Back or Flank Pain	5.38%	5.41%	p>0.05
Medical Device or Treatment Issue	1.14%	1.22%	p>0.05
Gastrointestinal Issues	6.75%	6.77%	p>0.05
Ear Complaints	0.85%	0.47%	p>0.05
Other Pain	2.06%	1.78%	p>0.05
Post-Op Issue	0.83%	0.73%	p>0.05
Psychiatric Complaints	0.47%	0.55%	p>0.05
Substance Abuse Issues	0.33%	0.51%	p>0.05
Breast Complaints	0.04%	0.11%	p>0.05
Medication Request	0.11%	0.16%	p>0.05
Unknown	0.13%	0.02%	p>0.05
Exposures, Bites, and Envenomations	0.33%	0.46%	p>0.05
Circulatory Issue	0.07%	0.07%	p>0.05

Table EC.9 Summary of chief complaints reported at triage in the pre-trial and post trial periods. We report the percentage prevalence of each binary variable, along with p-values derived from the chi-squared test. P-values>0.05 suggest no significant differences in the distributions between the two periods. P-values>0.05 suggest no significant differences in the distributions between the two periods.

MD ID	Pre-Trial (N = 5,522)	Trial (N = 5,493)	p-value
A	4.84%	3.73%	p<0.001
AA	2.03%	2.55%	p<0.05
AB	1.96%	1.84%	p>0.05
AC	1.83%	2.04%	p<0.05
AD	1.70%	0.86%	p<0.001
AE	1.70%	2.77%	p<0.001
AF	1.68%	2.60%	p<0.001
AG	1.56%	1.38%	p<0.001
AH	1.30%	0.75%	p<0.01
AI	1.01%	0.55%	p<0.01
AJ	0.69%	3.90%	p<0.001
AK	0.53%	1.00%	p<0.05
B	4.24%	3.90%	p<0.05
C	4.15%	3.51%	p<0.001
D	3.89%	3.82%	p>0.05
E	3.71%	4.35%	p<0.001
F	3.68%	3.09%	p>0.05
G	3.62%	3.82%	p<0.05
H	3.57%	3.48%	p>0.05
I	3.53%	3.11%	p>0.05
J	3.53%	2.35%	p<0.001
K	3.51%	3.79%	p>0.05
L	3.44%	3.68%	p>0.05
M	3.26%	3.79%	p>0.05
N	3.24%	2.71%	p>0.05
O	3.04%	3.44%	p<0.05
P	3.01%	3.08%	p>0.05
Q	2.95%	3.33%	p>0.05
R	2.90%	2.77%	p>0.05
S	2.90%	2.59%	p>0.05
T	2.79%	1.51%	p<0.001
U	2.44%	2.35%	p>0.05
V	2.44%	1.80%	p<0.001
W	2.43%	2.68%	p>0.05
X	2.41%	2.29%	p>0.05
Y	2.37%	2.28%	p<0.001
Z	2.12%	2.53%	p>0.05

Table EC.10 Summary of attending physician assignments in the pre-trial and post trial periods. We report the percentage prevalence of each binary variable, along with p-values derived from the chi-squared test. P-values>0.05 suggest no significant differences in the distributions between the two periods.

Variable	**Pre-Trial (N = 34 days)**	**Trial (N = 34 days)**	**p-value**
Nurses Hours (day)	537.54 (30.16)	521.30 (32.82)	$p < 0.05$
Nurse Shifts (day)	44.62 (2.23)	43.26 (2.43)	$p < 0.05$
MD Hours (day)	111.75 (6.32)	113.90 (7.77)	$p > 0.05$
MD Shifts (day)	13.15 (0.74)	13.40 (0.91)	$p > 0.05$
ED Rooms Available (day)	56 (0)	56 (0)	$p > 0.05$
ED Rooms Utilized (day)	55.28 (3.00)	54.39 (4.42)	$p > 0.05$
Arrival rate (hour) (12am-6am)	12.26 (4.36)	11.94 (3.62)	$p > 0.05$
Arrival rate (hour) (6am-12pm)	51.44 (6.47)	48.80 (9.88)	$p > 0.05$
Arrival rate (hour) (12pm-6pm)	63.88 (10.45)	59.40 (11.00)	$p > 0.05$
Arrival rate (hour) (6pm-12am)	34.82 (7.28)	36.80 (9.59)	$p > 0.05$
Discharge rate (hour) (12am-6am)	5.12 (2.37)	5.14 (2.39)	$p > 0.05$
Discharge rate (hour) (6am-12pm)	16.21 (4.39)	17.14 (3.66)	$p > 0.05$
Discharge rate (hour) (12pm-6pm)	58.56 (5.85)	55.51 (7.83)	$p > 0.05$
Discharge rate (hour) (6pm-12am)	82.53 (15.35)	79.14 (16.80)	$p > 0.05$
Patients in the ED (12am-6am)	4.80 (2.10)	4.78 (1.89)	$p > 0.05$
Patients in the ED (6am-12pm)	19.83 (3.48)	19.53 (4.41)	$p > 0.05$
Patients in the ED (12pm-6pm)	50.31 (7.68)	44.41 (11.48)	$p < 0.05$
Patients in the ED (6pm-12am)	35.28 (8.54)	32.74 (8.90)	$p > 0.05$
Patients in treatment in the ED (12am-6am)	3.47 (1.64)	3.43 (1.45)	$p > 0.05$
Patients in treatment in the ED (6am-12pm)	14.09 (2.33)	13.77 (2.83)	$p > 0.05$
Patients in treatment in the ED (12pm-6pm)	29.34 (3.77)	26.10 (5.06)	$p < 0.01$
Patients in treatment in the ED (6pm-12am)	18.26 (4.01)	16.98 (4.34)	$p > 0.05$
Patients waiting for discharge (12am-6am)	0.96 (0.51)	0.95 (0.50)	$p > 0.05$
Patients waiting for discharge (6am-12pm)	3.37 (1.18)	3.33 (1.15)	$p > 0.05$
Patients waiting for discharge (12pm-6pm)	14.42 (3.32)	13.31 (4.25)	$p > 0.05$
Patients waiting for discharge (6pm-12am)	14.27 (4.62)	13.07 (4.63)	$p > 0.05$
Patients in VPP (12am-6am)	0.00 (0.00)	0.00 (0.01)	$p > 0.05$
Patients in VPP (6am-12pm)	0.05 (0.10)	0.36 (0.16)	$p < 0.001$
Patients in VPP (12pm-6pm)	0.20 (0.25)	0.52 (0.21)	$p < 0.001$
Patients in VPP (6pm-12am)	0.04 (0.07)	0.16 (0.13)	$p < 0.001$

Table EC.11 Summary of operational ED characteristics and patient arrival patterns aggregated at the daily level in the pre-trial and trial periods. The mean and the standard deviation (in parentheses) are included for continuous variables and the percentage prevalence for binary variables, along with p-values derived from t-tests and chi-squared tests respectively. P-values>0.05 suggest no significant differences in the distributions between the two periods.

EC.6. Matching Models Summary

In this section, we provide additional information regarding the matching approaches we performed, and subsequently, we present summary tables of the resulting datasets.

Cardinality Matching: Cardinality matching is a robust approach employed to enhance the accuracy of effect estimations in observational studies. The method, proposed by Zubizarreta et al. (2014), uses mixed integer optimization to create a balanced sample. We apply the implementation of the R package "designmatch" (Zubizarreta et al. 2018). This approach offers different types of matching including exact matching and fine balancing for categorical variables, and moment balancing for continuous variables.

Exact matching involves selecting subsets of treated and control units such that each treated unit has a corresponding control unit with identical values for all covariates of interest. This method is stringent, ensuring that the groups are perfectly balanced on all observed covariates at the expense of significantly reducing the the number of units included in the final matched sample. Fine balancing balances the marginal distributions of covariates across treated and control groups. Thus, it ensures that the overall distribution of each covariate is similar between the two groups, allowing for greater flexibility in the matching process. Moment balancing seeks to ensure that the statistical moments of covariates are balanced between the treated and control groups, targeting balanced statistical properties of the covariates. For this reason, moment balancing is preferred for continuous variables.

In addition to "Matching on MD," we derive a second dataset based on the cardinality matching algorithm that will serve as sensitivity analysis for our empirical results. Specifically, we apply cardinality matching with: exact matching on the ESI level, chief complaint category expressed by the patient at the time of triage, and medical shift at arrival; moment balancing in terms of mean and variance for the number of patients in waiting and treatment; and distributional balancing via fine balance for the number of MDs and nurses on shift, types of procedures and tests administered, and the ED disposition of the patient. In comparison with the previous dataset, in the list of variables for exact matching we replace the attending physician with the chief complaint category, emphasizing more the medical condition rather than the provider. The output dataset, which we refer to as "Matching on CC," comprises $N = 5,976$ observations.

Propensity Score Matching: Propensity score matching serves as an additional supplementary sensitivity analysis for our empirical findings (Rosenbaum and Rubin 1983). To this end, we used logistic regression to estimate each patient's probability of being in the trial period based on the observed covariates. The model specification is given in Equation EC.11.

$$\log\left(\frac{\Pr(Trial_i)}{1-\Pr(Trial_i)}\right) = \alpha_0 + \boldsymbol{\beta}\mathbf{X}_i + \boldsymbol{\gamma}\mathbf{MD}_i + \boldsymbol{\delta}\mathbf{CC}_i. \tag{EC.11}$$

The vector $\mathbf{X}$ includes all variables presented in Table 4. A list of all chief complaints and MD assignments considered are available in Tables EC.9 and EC.10, respectively. Subsequently, for each patient in the trial period, we used the k-nearest neighbors algorithm to identify the most similar observation in the pre-trial period based on the computed propensity score (Fix 1985). Finally, we created matched pairs of observations using the identified neighbors ensuring balance in the likelihood of participating in the pre-trial and the trial periods. The resulting dataset includes $N = 10,926$ observations.

Dataset Summary Tables after Matching

Variable	**Pre-Trial (N=2,579)**	**Trial (N=2,579)**	**p-value**
ESI 1	0.00 (0.06)	0.00 (0.06)	p>0.05
ESI 2	0.26 (0.44)	0.26 (0.44)	p>0.05
ESI 3	0.55 (0.50)	0.55 (0.50)	p>0.05
ESI 4	0.19 (0.39)	0.19 (0.39)	p>0.05
ESI 5	0.00 (0.03)	0.00 (0.03)	p>0.05
Age	58.95 (20.78)	58.55 (20.90)	p>0.05
IV	0.64 (0.48)	0.65 (0.48)	p>0.05
CT with IVcontrast	0.24 (0.43)	0.23 (0.42)	p>0.05
CT without IV contrast	0.19 (0.39)	0.19 (0.39)	p>0.05
MRI	0.02 (0.14)	0.02 (0.14)	p>0.05
Xray	0.45 (0.50)	0.45 (0.50)	p>0.05
Ultrasound	0.12 (0.32)	0.13 (0.34)	p>0.05
Nurses on shift	24.34 (6.06)	24.09 (6.08)	p>0.05
MDs on shift	5.45 (1.97)	5.50 (2.02)	p>0.05
Current waiting count	4.28 (3.48)	4.27 (3.47)	p>0.05
Current treatment count	30.94 (14.31)	30.85 (14.31)	p>0.05
Shift: 12 am-6 am	0.09 (0.29)	0.09 (0.29)	p>0.05
Shift: 12 pm-6 pm	0.35 (0.48)	0.35 (0.48)	p>0.05
Shift: 6 am-12 pm	0.32 (0.47)	0.32 (0.47)	p>0.05
Shift: 6 pm-12 am	0.24 (0.42)	0.24 (0.43)	p>0.05
ED Disposition Admit	0.19 (0.39)	0.18 (0.38)	p>0.05
ED Disposition Discharge	0.67 (0.47)	0.68 (0.47)	p>0.05

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Table EC.12 continued from previous page

Variable	Pre-Trial	Trial	p-value
ED Disposition Hospital Observation	0.12 (0.32)	0.13 (0.34)	p>0.05
ED Disposition Left Without Being Seen/AMA	0.00 (0.06)	0.01 (0.08)	p>0.05
ED Disposition Transfer to Health Care Facility	0.01 (0.11)	0.01 (0.10)	p>0.05
MD_A	0.04 (0.20)	0.04 (0.19)	p>0.05
MD_AA	0.01 (0.11)	0.01 (0.10)	p>0.05
MD_AB	0.02 (0.13)	0.01 (0.12)	p>0.05
MD_AC	0.02 (0.16)	0.03 (0.16)	p>0.05
MD_AD	0.02 (0.15)	0.01 (0.12)	p<0.01
MD_AE	0.02 (0.13)	0.03 (0.18)	p<0.001
MD_AF	0.02 (0.14)	0.03 (0.16)	p<0.05
MD_AG	0.01 (0.09)	0.01 (0.09)	p>0.05
MD_AH	0.02 (0.13)	0.01 (0.09)	p<0.01
MD_AI	0.02 (0.12)	0.01 (0.10)	p>0.05
MD_AJ	0.01 (0.11)	0.04 (0.20)	p<0.001
MD_AK	0.01 (0.08)	0.01 (0.12)	p<0.01
MD_B	0.04 (0.19)	0.04 (0.19)	p>0.05
MD_C	0.03 (0.18)	0.03 (0.18)	p>0.05
MD_D	0.03 (0.18)	0.03 (0.18)	p>0.05
MD_E	0.05 (0.21)	0.05 (0.22)	p>0.05
MD_F	0.03 (0.18)	0.03 (0.16)	p>0.05
MD_G	0.04 (0.18)	0.03 (0.18)	p>0.05
MD_H	0.03 (0.17)	0.03 (0.17)	p>0.05
MD_I	0.05 (0.21)	0.04 (0.20)	p>0.05
MD_J	0.03 (0.18)	0.03 (0.17)	p>0.05
MD_K	0.04 (0.20)	0.04 (0.20)	p>0.05
MD_L	0.05 (0.21)	0.04 (0.20)	p>0.05
MD_M	0.04 (0.19)	0.03 (0.18)	p>0.05
MD_N	0.02 (0.13)	0.02 (0.14)	p>0.05
MD_O	0.02 (0.15)	0.03 (0.16)	p>0.05
MD_P	0.02 (0.15)	0.03 (0.16)	p>0.05
MD_Q	0.04 (0.19)	0.04 (0.20)	p>0.05
MD_R	0.03 (0.16)	0.02 (0.15)	p>0.05
MD_S	0.03 (0.18)	0.03 (0.18)	p>0.05
MD_T	0.03 (0.17)	0.02 (0.14)	p<0.05
MD_U	0.02 (0.13)	0.02 (0.12)	p>0.05
MD_V	0.01 (0.10)	0.01 (0.10)	p>0.05
MD_W	0.03 (0.17)	0.03 (0.16)	p>0.05
MD_X	0.02 (0.15)	0.02 (0.14)	p>0.05
MD_Y	0.03 (0.17)	0.02 (0.15)	p>0.05
MD_Z	0.03 (0.17)	0.03 (0.18)	p>0.05
Abdominal Complaints	0.12 (0.33)	0.12 (0.32)	p>0.05
Abnormal Test Results	0.04 (0.21)	0.05 (0.22)	p>0.05
Allergic Reaction	0.01 (0.09)	0.00 (0.07)	p>0.05
Back or Flank Pain	0.06 (0.23)	0.05 (0.22)	p>0.05
Breast Complaints	0.00 (0.00)	0.00 (0.04)	p<0.05
Cardiac Arrhythmias	0.02 (0.14)	0.03 (0.16)	p>0.05
Chest Pain	0.08 (0.27)	0.07 (0.26)	p>0.05
Circulatory Issue	0.00 (0.00)	0.00 (0.03)	p>0.05
Dizziness/Lightheadedness/Syncope	0.03 (0.17)	0.04 (0.19)	p>0.05
Ear Complaints	0.01 (0.10)	0.01 (0.08)	p>0.05
Epistaxis	0.01 (0.07)	0.01 (0.08)	p>0.05
Exposures, Bites, and Envenomations	0.01 (0.07)	0.01 (0.07)	p>0.05

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Table EC.12 continued from previous page

Variable	Pre-Trial	Trial	p-value
Extremity Complaints	0.10 (0.30)	0.11 (0.31)	p>0.05
Eye Complaints	0.02 (0.12)	0.02 (0.12)	p>0.05
Falls, Motor Vehicle Crashes, Assaults, and Trauma	0.05 (0.22)	0.05 (0.22)	p>0.05
Fatigue and Weakness	0.03 (0.18)	0.03 (0.16)	p>0.05
Fevers, Sweats or Chills	0.03 (0.17)	0.03 (0.16)	p>0.05
Foreign Body	0.00 (0.05)	0.00 (0.04)	p>0.05
Gastrointestinal Issues	0.06 (0.24)	0.06 (0.24)	p>0.05
Genital Complaints	0.02 (0.12)	0.02 (0.14)	p>0.05
Medical Device or Treatment Issue	0.01 (0.11)	0.01 (0.12)	p>0.05
Medication Request	0.00 (0.02)	0.00 (0.03)	p>0.05
Neurological Issue	0.06 (0.23)	0.06 (0.24)	p>0.05
Other	0.01 (0.08)	0.01 (0.10)	p>0.05
Other Pain	0.02 (0.15)	0.02 (0.15)	p>0.05
Post-Op Issue	0.01 (0.10)	0.01 (0.09)	p>0.05
Psychiatric Complaints	0.01 (0.08)	0.01 (0.07)	p>0.05
Shortness of Breath	0.06 (0.24)	0.06 (0.24)	p>0.05
Skin Complaints	0.05 (0.22)	0.05 (0.22)	p>0.05
Substance Abuse Issues	0.00 (0.06)	0.01 (0.07)	p>0.05
Upper Respiratory Symptoms	0.05 (0.22)	0.04 (0.20)	p>0.05
Urinary Complaints	0.03 (0.16)	0.03 (0.17)	p>0.05

Table EC.12: Dataset summary after cardinality matching based on MD.

Variable	Pre-Trial (N=2,988)	Trial (N=2,988)	p-value
ESI 1	0.00 (0.05)	0.00 (0.05)	p>0.05
ESI 2	0.22 (0.41)	0.22 (0.41)	p>0.05
ESI 3	0.64 (0.48)	0.64 (0.48)	p>0.05
ESI 4	0.13 (0.34)	0.13 (0.34)	p>0.05
ESI 5	0.00 (0.03)	0.00 (0.03)	p>0.05
Age	58.56 (20.90)	58.17 (20.79)	p>0.05
IV	0.66 (0.47)	0.67 (0.47)	p>0.05
CT with IVcontrast	0.26 (0.44)	0.26 (0.44)	p>0.05
CT without IV contrast	0.20 (0.40)	0.19 (0.40)	p>0.05
MRI	0.02 (0.13)	0.02 (0.14)	p>0.05
Xray	0.44 (0.50)	0.43 (0.50)	p>0.05
ultrasound	0.12 (0.33)	0.13 (0.34)	p>0.05
Nurses on shift	24.51 (5.98)	24.24 (5.99)	p>0.05
MDs on shift	5.54 (1.96)	5.56 (1.97)	p>0.05
Current waiting count	4.40 (3.54)	4.38 (3.52)	p>0.05
Current treatment count	31.50 (14.03)	31.45 (14.01)	p>0.05
Shift: 12 am-6 am	0.07 (0.26)	0.07 (0.26)	p>0.05
Shift: 12 pm-6 pm	0.36 (0.48)	0.36 (0.48)	p>0.05
Shift: 6 am-12 pm	0.33 (0.47)	0.33 (0.47)	p>0.05
Shift: 6 pm-12 am	0.24 (0.43)	0.24 (0.43)	p>0.05
ED Disposition Admit	0.19 (0.39)	0.18 (0.39)	p>0.05
ED Disposition Discharge	0.68 (0.47)	0.68 (0.47)	p>0.05
ED Disposition Hospital Observation	0.12 (0.32)	0.12 (0.33)	p>0.05

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Table EC.13 continued from previous page

Variable	**Pre-Trial**	**Trial**	**p-value**
ED Disposition Left Without Being Seen/AMA	0.00 (0.07)	0.01 (0.08)	p>0.05
ED Disposition Transfer to Health Care Facility	0.01 (0.11)	0.01 (0.10)	p>0.05
Abdominal Complaints	0.17 (0.38)	0.17 (0.38)	p>0.05
Abnormal Test Results	0.05 (0.21)	0.05 (0.21)	p>0.05
Allergic Reaction	0.01 (0.08)	0.00 (0.07)	p>0.05
Back or Flank Pain	0.06 (0.24)	0.06 (0.24)	p>0.05
Breast Complaints	0.00 (0.00)	0.00 (0.03)	p>0.05
Cardiac Arrhythmias	0.02 (0.13)	0.02 (0.13)	p>0.05
Chest Pain	0.08 (0.28)	0.08 (0.28)	p>0.05
Circulatory Issue	0.00 (0.03)	0.00 (0.03)	p>0.05
Dizziness/Lightheadedness/Syncope	0.03 (0.17)	0.03 (0.17)	p>0.05
Ear Complaints	0.01 (0.10)	0.01 (0.07)	p<0.05
Epistaxis	0.00 (0.07)	0.01 (0.08)	p>0.05
Exposures, Bites, and Envenomations	0.00 (0.05)	0.01 (0.08)	p>0.05
Extremity Complaints	0.11 (0.31)	0.11 (0.31)	p>0.05
Eye Complaints	0.01 (0.09)	0.01 (0.08)	p>0.05
Falls, Motor Vehicle Crashes, Assaults, and Trauma	0.04 (0.20)	0.04 (0.20)	p>0.05
Fatigue and Weakness	0.02 (0.12)	0.02 (0.12)	p>0.05
Fevers, Sweats or Chills	0.01 (0.12)	0.01 (0.12)	p>0.05
Foreign Body	0.00 (0.04)	0.00 (0.04)	p>0.05
Gastrointestinal Issues	0.07 (0.26)	0.07 (0.26)	p>0.05
Genital Complaints	0.01 (0.10)	0.01 (0.10)	p>0.05
Medical Device or Treatment Issue	0.01 (0.09)	0.01 (0.09)	p>0.05
Medication Request	0.00 (0.02)	0.00 (0.03)	p>0.05
Neurological Issue	0.07 (0.25)	0.07 (0.25)	p>0.05
Other	0.01 (0.10)	0.01 (0.09)	p>0.05
Other Pain	0.02 (0.12)	0.01 (0.12)	p>0.05
Post-Op Issue	0.01 (0.08)	0.01 (0.08)	p>0.05
Psychiatric Complaints	0.01 (0.08)	0.01 (0.08)	p>0.05
Shortness of Breath	0.07 (0.25)	0.07 (0.25)	p>0.05
Skin Complaints	0.04 (0.20)	0.04 (0.20)	p>0.05
Substance Abuse Issues	0.00 (0.06)	0.01 (0.08)	p>0.05
Upper Respiratory Symptoms	0.04 (0.19)	0.04 (0.19)	p>0.05
Urinary Complaints	0.03 (0.17)	0.03 (0.17)	p>0.05

Table EC.13: Dataset summary after cardinality matching based on CC.

Variable	**Pre-Trial (N=5,463)**	**Trial (N=5,463)**	**p-value**
ESI 1	0.00 (0.07)	0.01 (0.08)	p>0.05
ESI 2	0.24 (0.43)	0.24 (0.43)	p>0.05
ESI 3	0.60 (0.49)	0.61 (0.49)	p>0.05
ESI 4	0.15 (0.35)	0.14 (0.35)	p>0.05
ESI 5	0.00 (0.07)	0.00 (0.06)	p>0.05
Age	59.02 (20.76)	58.62 (20.90)	p>0.05
IV	0.66 (0.47)	0.66 (0.47)	p>0.05
CT with IVcontrast	0.24 (0.43)	0.25 (0.43)	p>0.05
CT without IV contrast	0.21 (0.41)	0.20 (0.40)	p<0.05

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Table EC.14 continued from previous page

Variable	Pre-Trial	Trial	p-value
MRI	0.02 (0.14)	0.02 (0.14)	p>0.05
Xray	0.44 (0.50)	0.44 (0.50)	p>0.05
ultrasound	0.13 (0.34)	0.13 (0.33)	p>0.05
Nurses on shift	24.24 (6.13)	24.29 (6.08)	p>0.05
Current waiting count	4.55 (3.86)	4.65 (3.92)	p>0.05
Current treatment count	31.16 (14.59)	31.25 (14.31)	p>0.05
Shift: 12 am-6 am	0.07 (0.26)	0.07 (0.26)	p>0.05
Shift: 12 pm-6 pm	0.37 (0.48)	0.38 (0.49)	p>0.05
Shift: 6 am-12 pm	0.33 (0.47)	0.31 (0.46)	p>0.05
Shift: 6 pm-12 am	0.24 (0.43)	0.24 (0.42)	p>0.05
ED Disposition Admit	0.20 (0.40)	0.19 (0.39)	p>0.05
ED Disposition Discharge	0.66 (0.47)	0.67 (0.47)	p>0.05
ED Disposition Hospital Observation	0.13 (0.33)	0.12 (0.33)	p>0.05
ED Disposition Left Without Being Seen/AMA	0.01 (0.08)	0.01 (0.08)	p>0.05
ED Disposition Transfer to Health Care Facility	0.01 (0.09)	0.01 (0.10)	p>0.05
Abdominal Complaints	0.12 (0.33)	0.13 (0.34)	p>0.05
Abnormal Test Results	0.05 (0.22)	0.05 (0.22)	p>0.05
Allergic Reaction	0.00 (0.06)	0.00 (0.06)	p>0.05
Back or Flank Pain	0.06 (0.23)	0.05 (0.23)	p>0.05
Breast Complaints	0.00 (0.02)	0.00 (0.03)	p>0.05
Cardiac Arrhythmias	0.03 (0.17)	0.02 (0.15)	p>0.05
Chest Pain	0.07 (0.26)	0.07 (0.26)	p>0.05
Circulatory Issue	0.00 (0.03)	0.00 (0.03)	p>0.05
Dizziness/Lightheadedness/Syncope	0.04 (0.20)	0.04 (0.19)	p>0.05
Ear Complaints	0.00 (0.06)	0.00 (0.07)	p>0.05
Epistaxis	0.01 (0.08)	0.01 (0.08)	p>0.05
Exposures, Bites, and Envenomations	0.00 (0.06)	0.00 (0.07)	p>0.05
Extremity Complaints	0.09 (0.29)	0.10 (0.30)	p>0.05
Eye Complaints	0.02 (0.15)	0.02 (0.12)	p<0.05
Falls, Motor Vehicle Crashes, Assaults, and Trauma	0.06 (0.23)	0.05 (0.22)	p>0.05
Fatigue and Weakness	0.04 (0.19)	0.03 (0.17)	p>0.05
Fevers, Sweats or Chills	0.03 (0.16)	0.03 (0.16)	p>0.05
Foreign Body	0.00 (0.04)	0.00 (0.03)	p>0.05
Gastrointestinal Issues	0.07 (0.25)	0.07 (0.25)	p>0.05
Genital Complaints	0.01 (0.12)	0.01 (0.12)	p>0.05
Medical Device or Treatment Issue	0.01 (0.11)	0.01 (0.11)	p>0.05
Medication Request	0.00 (0.05)	0.00 (0.04)	p>0.05
Neurological Issue	0.06 (0.23)	0.06 (0.24)	p>0.05
Other Pain	0.02 (0.14)	0.02 (0.13)	p>0.05
Post-Op Issue	0.01 (0.09)	0.01 (0.09)	p>0.05
Psychiatric Complaints	0.00 (0.06)	0.01 (0.07)	p>0.05
Shortness of Breath	0.06 (0.25)	0.06 (0.24)	p>0.05
Skin Complaints	0.05 (0.21)	0.05 (0.21)	p>0.05
Substance Abuse Issues	0.01 (0.08)	0.01 (0.07)	p>0.05
Unknown	0.00 (0.03)	0.00 (0.00)	p<0.05
Upper Respiratory Symptoms	0.04 (0.19)	0.04 (0.19)	p>0.05
Urinary Complaints	0.03 (0.17)	0.03 (0.17)	p>0.05
Propensity score	0.54 (0.13)	0.54 (0.13)	p>0.05

Table EC.14: Dataset summary after propensity score matching.

EC.7. Empirical Models Summary

In this section, we summarize our results from the empirical models that we developed to measure the impact of the proposed VPP protocol during the implementation trial at the new Mayo ED.

Across all tables, the significance levels are denoted as follows: a p-value < 0.05 is marked with a single asterisk (*), indicating moderate evidence against the null hypothesis. A p-value < 0.01 is marked with two asterisks (**), representing strong evidence against the null hypothesis. Finally, a p-value < 0.001 is denoted by three asterisks (***), indicating very strong evidence against the null hypothesis. All p-values ≥ 0.05 are not marked.

EC.7.1. Consolidated Results for Trial Effect

	Mathing on CC			**Propensity score matching**		
Model	A	B	C	A	B	C
Trial Coef.	-0.057*** (0.013)	-0.057*** (0.013)	-0.047*** (0.013)	-0.024* (0.01)	-0.022* (0.01)	-0.022* (0.01)
Attending MD	yes	yes	no	yes	yes	no
CC Category	yes	no	no	yes	no	no
Sample size	5,976	5,976	5,976	10,926	10,926	10,926
R^2	0.419	0.405	0.336	0.438	0.42	0.344
F	48.881	70.024	132.687	95.582	134.895	250.151

Table EC.15 Supplementary empirical models summary for the dependent variable "log time from arrival to disposition." The attending MD and CC category rows indicate whether the models controlled for these variables.

	Mathing on CC			**Propensity score matching**		
Model	A	B	C	A	B	C
Trial Coef.	-0.045*** (0.009)	-0.045*** (0.009)	-0.039*** (0.01)	-0.027*** (0.007)	-0.026*** (0.007)	-0.026*** (0.007)
Attending MD	yes	yes	no	yes	yes	no
CC Category	yes	no	no	yes	no	no
Sample size	5,976	5,976	5,976	10,926	10,926	10,926
R^2	0.513	0.502	0.464	0.533	0.52	0.478
F	70.948	103.162	225.586	139.762	201.962	435.76

Table EC.16 Supplementary empirical models summary for the dependent variable "log time from arrival to ED departure." The attending MD and CC category rows indicate whether the models controlled for these variables.

	No Matching			Matching on MD		
Model	A	B	C	A	B	C
Trial Coef.	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.003 (0.004)	-0.002 (0.004)	-0.003 (0.004)
Attending MD	yes	yes	no	yes	yes	no
CC Category	yes	no	no	yes	no	no
Sample size	11,015	11,015	11,015	5,158	5,158	5,158
R^2	0.017	0.013	0.012	0.025	0.017	0.016
F	3.024	3.357	6.909	2.469	2.476	4.595

Table EC.17 Primary empirical models summary for the dependent variable "ED return within 72 hours (with admission)." The attending MD and CC category rows indicate whether the models controlled for these variables.

	No Matching			Matching on MD		
Model	A	B	C	A	B	C
Trial Coef.	-0.001 (0.003)	-0.0 (0.003)	-0.0 (0.003)	0.002 (0.004)	0.002 (0.004)	0.003 (0.004)
Attending MD	yes	yes	no	yes	yes	no
CC Category	yes	no	no	yes	no	no
Sample size	11,015	11,015	11,015	5,158	5,158	5,158
R^2	0.017	0.008	0.007	0.015	0.008	0.005
F	3.108	2.428	4.254	1.864	1.715	2.207

Table EC.18 Primary empirical models summary for the dependent variable "ED return within 72 hours (without admission)." The attending MD and CC category rows indicate whether the models controlled for these variables.

	Mathing on CC			Propensity score matching		
Model	A	B	C	A	B	C
Trial Coef.	0.0 (0.004)	0.0 (0.004)	-0.001 (0.004)	-0.009 (0.003)	-0.009 (0.003)	-0.009 (0.003)
Attending MD	yes	yes	no	yes	yes	no
CC Category	yes	no	no	yes	no	no
Sample size	5,976	5,976	5,976	10,926	10,926	10,926
R^2	0.022	0.012	0.012	0.026	0.022	0.017
F	2.479	2.267	4.199	4.273	5.129	9.125

Table EC.19 Supplementary empirical models summary for the dependent variable "ED return within 72 hours (with admission)." The attending MD and CC category rows indicate whether the models controlled for these variables.

	Mathing on CC			Propensity score matching		
Model	A	B	C	A	B	C
Trial Coef.	0.002 (0.004)	0.002 (0.004)	0.002 (0.004)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
Attending MD	yes	yes	no	yes	yes	no
CC Category	yes	no	no	yes	no	no
Sample size	5,976	5,976	5,976	10,926	10,926	10,926
R^2	0.014	0.01	0.006	0.019	0.012	0.009
F	1.915	1.975	2.674	3.323	3.305	5.467

Table EC.20 Supplementary empirical models summary for the dependent variable "ED return within 72 hours (without admission)." The attending MD and CC category rows indicate whether the models controlled for these variables.

EC.7.2. Comprehensive Empirical Model Results

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	3.577*** (0.092)	4.159*** (0.068)	0.008 (0.028)	0.023 (0.028)
ESI 1	0.2* (0.094)	0.219** (0.069)	0.037 (0.028)	0.042 (0.029)
ESI 2	0.786*** (0.071)	0.653*** (0.052)	0.031 (0.021)	0.022 (0.022)
ESI 3	0.803*** (0.071)	0.669*** (0.052)	0.022 (0.021)	0.024 (0.022)
ESI 4	0.575*** (0.071)	0.497*** (0.052)	0.015 (0.021)	0.02 (0.022)
Patient Age	0.001*** (0.0)	0.001*** (0.0)	0.0* (0.0)	-0.0 (0.0)
Trial	-0.044*** (0.01)	-0.037*** (0.007)	-0.002 (0.003)	-0.001 (0.003)
IV	0.326*** (0.013)	0.285*** (0.01)	0.016*** (0.004)	-0.001 (0.004)
CT with IVcontrast	0.363*** (0.013)	0.238*** (0.01)	-0.013*** (0.004)	-0.007. (0.004)
CT without IV contrast	0.259*** (0.013)	0.182*** (0.01)	-0.004 (0.004)	0.003 (0.004)
MRI	0.286*** (0.034)	0.248*** (0.025)	-0.028** (0.01)	0.011 (0.011)
Xray	0.187*** (0.012)	0.144*** (0.009)	-0.000036	-0.006 (0.004)
Ultrasound	0.228*** (0.015)	0.195*** (0.011)	0.001 (0.005)	-0.001 (0.005)
Nurses on shift	0.001 (0.002)	-0.000003	0.001 (0.001)	-0.0 (0.001)
MDs on shift	-0.026*** (0.006)	-0.022*** (0.004)	0.0 (0.002)	0.002 (0.002)
Current waiting count	0.004** (0.001)	0.014*** (0.001)	0.0 (0.0)	0.0 (0.0)
Current treatment count	0.004*** (0.001)	0.006*** (0.001)	-0.0 (0.0)	-0.0 (0.0)
Shift: 6 am-12 pm	0.155*** (0.025)	0.058** (0.019)	-0.013. (0.008)	-0.005 (0.008)
Shift: 12 pm-6 pm	0.019 (0.033)	-0.03 (0.024)	-0.007 (0.01)	-0.012 (0.01)
Shift: 6 pm-12 am	-0.024 (0.028)	-0.064** (0.021)	-0.01 (0.009)	-0.006 (0.009)
ED Disposition Admit	-0.195*** (0.015)	0.14*** (0.011)	0.007. (0.004)	-0.026*** (0.004)
ED Disposition Hospital Observation	-0.002 (0.016)	0.235*** (0.012)	-0.005 (0.005)	-0.019*** (0.005)
ED Disposition Left Without Being Seen/AMA	-0.027 (0.065)	-0.005217	0.161*** (0.019)	0.037. (0.02)
ED Disposition Transfer to Health Care Facility	0.124** (0.045)	0.394*** (0.033)	-0.015 (0.014)	-0.026. (0.014)
MD_A	0.148*** (0.023)	0.121*** (0.017)	-0.003 (0.007)	0.004 (0.007)
MD_AA	0.232*** (0.031)	0.264*** (0.023)	-0.011 (0.009)	-0.00019
MD_AB	0.222*** (0.034)	0.205*** (0.025)	0.006 (0.01)	-0.001 (0.01)
MD_AC	0.359*** (0.036)	0.286*** (0.027)	-0.011 (0.011)	-0.017 (0.011)
MD_AD	-0.003999	-0.054. (0.031)	0.008 (0.013)	0.005 (0.013)
MD_AE	-0.041 (0.032)	0.01 (0.023)	0.004 (0.009)	-0.006 (0.01)
MD_AF	0.003 (0.032)	0.031 (0.023)	-0.014 (0.01)	0.031** (0.01)
MD_AG	0.077* (0.038)	0.107*** (0.028)	-0.002 (0.011)	0.026* (0.012)
MD_AH	0.229*** (0.046)	0.21*** (0.033)	-0.0 (0.014)	0.0 (0.014)
MD_AI	0.285*** (0.055)	0.182*** (0.04)	0.013 (0.016)	0.025 (0.017)
MD_AJ	0.196*** (0.031)	0.165*** (0.023)	0.008 (0.009)	-0.003 (0.01)
MD_AK	0.311*** (0.053)	0.256*** (0.039)	0.011 (0.016)	0.012 (0.016)
MD_B	0.31*** (0.024)	0.249*** (0.017)	-0.007 (0.007)	-0.001 (0.007)

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Table EC.21 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
MD_C	0.2*** (0.024)	0.158*** (0.018)	-0.005 (0.007)	-0.000105
MD_D	0.328*** (0.024)	0.24*** (0.018)	0.008 (0.007)	-0.004 (0.007)
MD_E	-0.161*** (0.024)	-0.016 (0.018)	-0.011 (0.007)	0.011 (0.007)
MD_F	0.015 (0.026)	0.058** (0.019)	0.003 (0.008)	0.001 (0.008)
MD_G	0.313*** (0.024)	0.251*** (0.018)	0.011 (0.007)	-0.001 (0.008)
MD_H	0.169*** (0.025)	0.15*** (0.018)	-0.002 (0.008)	-0.004 (0.008)
MD_I	-0.141*** (0.026)	-0.051** (0.019)	0.005 (0.008)	-0.01 (0.008)
MD_J	-0.185*** (0.027)	-0.034. (0.02)	0.003 (0.008)	0.007 (0.008)
MD_K	0.185*** (0.025)	0.149*** (0.018)	-0.009 (0.007)	0.0 (0.008)
MD_L	0.094*** (0.025)	0.07*** (0.018)	0.007 (0.007)	0.001 (0.008)
MD_M	0.116*** (0.025)	0.106*** (0.018)	-0.000128	-0.006 (0.008)
MD_N	0.167*** (0.028)	0.166*** (0.02)	0.007 (0.008)	-0.0 (0.009)
MD_O	0.134*** (0.026)	0.16*** (0.019)	0.001 (0.008)	-0.001 (0.008)
MD_P	0.164*** (0.027)	0.159*** (0.02)	-0.006 (0.008)	-0.001 (0.008)
MD_Q	-0.28*** (0.027)	0.002 (0.019)	0.019* (0.008)	-0.008 (0.008)
MD_R	-0.117*** (0.028)	-0.006 (0.02)	0.011 (0.008)	0.005 (0.009)
MD_S	0.214*** (0.028)	0.183*** (0.021)	-0.007 (0.008)	-0.003 (0.009)
MD_T	-0.175*** (0.033)	-0.096*** (0.024)	-0.007 (0.01)	-0.0 (0.01)
MD_U	-0.017 (0.03)	0.073** (0.022)	0.005 (0.009)	0.013 (0.009)
MD_V	0.279*** (0.032)	0.23*** (0.024)	-0.013 (0.01)	-0.0002
MD_W	0.121*** (0.029)	0.1*** (0.021)	0.012 (0.009)	0.003 (0.009)
MD_X	-0.212*** (0.03)	-0.128*** (0.022)	0.005 (0.009)	0.0 (0.009)
MD_Y	0.195*** (0.031)	0.19*** (0.022)	0.003 (0.009)	-0.008 (0.009)
MD_Z	-0.002277	0.012 (0.024)	-0.015 (0.01)	0.005 (0.01)
Abdominal Complaints	0.043 (0.058)	0.013 (0.043)	-0.017 (0.017)	-0.008 (0.018)
Abnormal Test Results	-0.07 (0.061)	-0.002 (0.044)	-0.025 (0.018)	-0.002 (0.019)
Allergic Reaction	-0.125 (0.087)	-0.113. (0.064)	-0.024 (0.026)	-0.016 (0.027)
Back or Flank Pain	0.032 (0.06)	0.028 (0.044)	0.003 (0.018)	-0.003 (0.019)
Breast Complaints	-0.12 (0.183)	-0.052 (0.134)	-0.036 (0.055)	-0.029 (0.056)
Cardiac Arrhythmias	0.054 (0.065)	0.006 (0.047)	-0.033. (0.019)	-0.015 (0.02)
Chest Pain	0.038 (0.06)	-0.006 (0.044)	-0.019 (0.018)	-0.005 (0.018)
Circulatory Issue	-0.078 (0.183)	-0.108 (0.134)	0.307*** (0.055)	-0.027 (0.056)
Dizziness, Lightheadedness, Syncope	0.041 (0.062)	0.008 (0.045)	-0.025 (0.019)	-0.02 (0.019)
Ear Complaints	-0.302*** (0.081)	-0.214*** (0.06)	-0.029 (0.024)	-0.007 (0.025)
Epistaxis	0.051 (0.086)	0.047 (0.063)	-0.037 (0.026)	0.154*** (0.027)
Exposures, Bites, and Envenomations	-0.333*** (0.094)	-0.217** (0.069)	0.019 (0.028)	-0.033 (0.029)
Extremity Complaints	-0.084 (0.059)	-0.069 (0.043)	-0.019 (0.018)	-0.009 (0.018)
Eye Complaints	-0.125. (0.069)	-0.0062	-0.015 (0.021)	-0.003 (0.021)
Falls, Motor Vehicle Crashes, Assaults, and Trauma	-0.036 (0.061)	-0.018 (0.044)	-0.026 (0.018)	0.001 (0.019)

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Table EC.21 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Fatigue and Weakness	-0.026 (0.063)	0.0 (0.046)	-0.012 (0.019)	0.001 (0.019)
Fevers, Sweats or Chills	-0.106. (0.064)	-0.063 (0.046)	-0.031 (0.019)	-0.004 (0.02)
Foreign Body	-0.04116	-0.02652	-0.022 (0.042)	-0.034 (0.043)
Gastrointestinal Issues	-0.01 (0.059)	0.015 (0.044)	-0.019 (0.018)	0.003 (0.018)
Genital Complaints	0.155* (0.068)	0.096. (0.05)	-0.025 (0.02)	-0.022 (0.021)
Medical Device or Treatment Issue	-0.052 (0.071)	0.019 (0.052)	-0.015 (0.021)	0.012 (0.022)
Medication Request	-0.522*** (0.145)	-0.026394	-0.025 (0.043)	0.043 (0.044)
Neurological Issue	-0.036 (0.06)	-0.024 (0.044)	-0.023 (0.018)	0.001 (0.018)
Other Pain	-0.088 (0.066)	-0.052 (0.048)	-0.018 (0.02)	-0.004 (0.02)
Post-Op Issue	-0.246** (0.078)	-0.218*** (0.057)	-0.003 (0.023)	-0.013 (0.024)
Psychiatric Complaints	0.241** (0.089)	0.235*** (0.065)	-0.021 (0.027)	0.008 (0.027)
Shortness of Breath	-0.036 (0.06)	-0.005 (0.044)	-0.02 (0.018)	-0.002 (0.018)
Skin Complaints	-0.218*** (0.061)	-0.156*** (0.045)	-0.018 (0.018)	-0.006 (0.019)
Substance Abuse Issues	0.146 (0.092)	0.066 (0.068)	-0.029 (0.028)	0.013 (0.028)
Unknown	-0.5445	-1.192** (0.363)	-0.042 (0.148)	0.961*** (0.152)
Upper Respiratory Symptoms	-0.106. (0.061)	-0.00432	-0.006 (0.018)	-0.012 (0.019)
Urinary Complaints	0.037 (0.063)	0.062 (0.046)	0.004 (0.019)	0.03 (0.019)
Adjusted R^2	0.427	0.527	0.017	0.017
Sample size	11,015	11,015	11,015	11,015
F value	90.504	135.005	3.024	3.108

Table EC.21: No Matching: empirical model description for category A.

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	3.391*** (0.072)	4.026*** (0.053)	-0.006 (0.021)	0.024 (0.022)
ESI 1	0.384*** (0.091)	0.335*** (0.066)	0.028 (0.027)	0.038 (0.028)
ESI 2	0.967*** (0.067)	0.774*** (0.049)	0.026 (0.02)	0.019 (0.02)
ESI 3	0.979*** (0.066)	0.787*** (0.048)	0.02 (0.02)	0.02 (0.02)
ESI 4	0.69*** (0.067)	0.57*** (0.049)	0.015 (0.02)	0.015 (0.02)
Patient Age	0.001*** (0.0)	0.001*** (0.0)	0.0** (0.0)	-0.0 (0.0)
Trial	-0.042*** (0.01)	-0.035*** (0.007)	-0.002 (0.003)	-0.0 (0.003)
IV	0.344*** (0.013)	0.298*** (0.009)	0.017*** (0.004)	-0.002 (0.004)

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Table EC.22 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
CT with IV contrast	0.382*** (0.013)	0.244*** (0.009)	-0.013*** (0.004)	-0.000036
CT without IV contrast	0.273*** (0.012)	0.193*** (0.009)	-0.003 (0.004)	0.003 (0.004)
MRI	0.271*** (0.034)	0.234*** (0.025)	-0.027** (0.01)	0.011 (0.01)
Xray	0.185*** (0.01)	0.136*** (0.007)	-0.01*** (0.003)	-0.01** (0.003)
Ultrasound	0.239*** (0.015)	0.2*** (0.011)	0.0 (0.004)	-0.004 (0.005)
Nurses on shift	0.001 (0.002)	-0.000003	0.001 (0.001)	-0.0 (0.001)
MDs on shift	-0.027*** (0.006)	-0.023*** (0.004)	0.0 (0.002)	0.002 (0.002)
Current waiting count	0.004** (0.001)	0.014*** (0.001)	0.0 (0.0)	0.0 (0.0)
Current treatment count	0.004*** (0.001)	0.006*** (0.001)	-0.0 (0.0)	-0.0 (0.0)
Shift: 6 am-12 pm	0.148*** (0.026)	0.053** (0.019)	-0.014. (0.008)	-0.005 (0.008)
Shift: 12 pm-6 pm	0.013 (0.033)	-0.036 (0.024)	-0.009 (0.01)	-0.011 (0.01)
Shift: 6 pm-12 am	-0.034 (0.029)	-0.072*** (0.021)	-0.012 (0.009)	-0.005 (0.009)
ED Disposition Admit	-0.214*** (0.014)	0.135*** (0.011)	0.008. (0.004)	-0.024*** (0.004)
ED Disposition Hospital Observation	-0.006 (0.016)	0.232*** (0.012)	-0.006 (0.005)	-0.019*** (0.005)
ED Disposition Left Without Being Seen/AMA	-0.023 (0.065)	-0.005232	0.164*** (0.019)	0.035. (0.02)
ED Disposition Transfer to Health Care Facility	0.138** (0.045)	0.415*** (0.033)	-0.017 (0.013)	-0.023. (0.014)
MD_A	0.139*** (0.023)	0.116*** (0.017)	-0.004 (0.007)	0.003 (0.007)
MD_AA	0.227*** (0.031)	0.259*** (0.023)	-0.012 (0.009)	-0.0002
MD_AB	0.211*** (0.034)	0.198*** (0.025)	0.006 (0.01)	0.004 (0.01)
MD_AC	0.353*** (0.037)	0.281*** (0.027)	-0.012 (0.011)	-0.018 (0.011)
MD_AD	-0.004085	-0.059. (0.031)	0.008 (0.013)	0.003 (0.013)
MD_AE	-0.051 (0.032)	0.001 (0.023)	0.006 (0.009)	-0.009 (0.01)
MD_AF	-0.003 (0.032)	0.027 (0.023)	-0.015 (0.01)	0.031** (0.01)
MD_AG	0.065. (0.039)	0.1*** (0.028)	-0.003 (0.011)	0.026* (0.012)
MD_AH	0.225*** (0.046)	0.207*** (0.034)	-0.001 (0.014)	-0.001 (0.014)
MD_AI	0.274*** (0.055)	0.174*** (0.04)	0.012 (0.016)	0.026 (0.017)
MD_AJ	0.194*** (0.032)	0.163*** (0.023)	0.007 (0.009)	-0.001 (0.01)
MD_AK	0.306*** (0.053)	0.253*** (0.039)	0.009 (0.016)	0.012 (0.016)
MD_B	0.304*** (0.024)	0.246*** (0.017)	-0.007 (0.007)	-0.001 (0.007)
MD_C	0.199*** (0.024)	0.155*** (0.018)	-0.006 (0.007)	-0.000112
MD_D	0.324*** (0.024)	0.238*** (0.018)	0.008 (0.007)	-0.003 (0.007)
MD_E	-0.174*** (0.024)	-0.023 (0.018)	-0.011 (0.007)	0.012. (0.007)
MD_F	0.009 (0.026)	0.054** (0.019)	0.003 (0.008)	0.002 (0.008)
MD_G	0.314*** (0.025)	0.252*** (0.018)	0.011 (0.007)	0.0 (0.008)
MD_H	0.165*** (0.025)	0.148*** (0.019)	-0.003 (0.008)	-0.003 (0.008)
MD_I	-0.142*** (0.026)	-0.052** (0.019)	0.004 (0.008)	-0.012 (0.008)
MD_J	-0.195*** (0.028)	-0.0008	0.003 (0.008)	0.007 (0.008)
MD_K	0.185*** (0.025)	0.147*** (0.018)	-0.009 (0.007)	-0.0 (0.008)

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Table EC.22 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
MD_L	0.092*** (0.025)	0.069*** (0.018)	0.007 (0.007)	0.001 (0.008)
MD_M	0.111*** (0.025)	0.103*** (0.019)	-0.000136	-0.006 (0.008)
MD_N	0.159*** (0.028)	0.164*** (0.02)	0.006 (0.008)	0.0 (0.009)
MD_O	0.134*** (0.026)	0.16*** (0.019)	0.001 (0.008)	0.0 (0.008)
MD_P	0.155*** (0.027)	0.151*** (0.02)	-0.006 (0.008)	-0.002 (0.008)
MD_Q	-0.285*** (0.027)	-0.001 (0.02)	0.018* (0.008)	-0.008 (0.008)
MD_R	-0.122*** (0.028)	-0.011 (0.021)	0.012 (0.008)	0.004 (0.009)
MD_S	0.209*** (0.029)	0.178*** (0.021)	-0.007 (0.008)	-0.005 (0.009)
MD_T	-0.181*** (0.033)	-0.102*** (0.024)	-0.006 (0.01)	-0.0 (0.01)
MD_U	-0.018 (0.03)	0.073** (0.022)	0.005 (0.009)	0.015 (0.009)
MD_V	0.279*** (0.032)	0.232*** (0.024)	-0.014 (0.01)	-0.019. (0.01)
MD_W	0.116*** (0.03)	0.095*** (0.022)	0.013 (0.009)	0.003 (0.009)
MD_X	-0.215*** (0.031)	-0.13*** (0.022)	0.004 (0.009)	0.002 (0.009)
MD_Y	0.194*** (0.031)	0.191*** (0.023)	0.002 (0.009)	-0.008 (0.009)
MD_Z	-0.00238	0.011 (0.025)	-0.016 (0.01)	0.006 (0.01)
Adjusted R^2	0.414	0.516	0.013	0.008
Sample size	11,015	11,015	11,015	11,015
F value	131.849	198.889	3.357	2.428

Table EC.22: No Matching: empirical model description for category B.

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	3.456*** (0.077)	4.102*** (0.055)	-0.011 (0.021)	0.021 (0.022)
ESI 1	0.387*** (0.096)	0.335*** (0.069)	0.03 (0.027)	0.04 (0.028)
ESI 2	0.976*** (0.071)	0.776*** (0.051)	0.026 (0.02)	0.019 (0.02)
ESI 3	0.988*** (0.07)	0.788*** (0.05)	0.02 (0.02)	0.021 (0.02)
ESI 4	0.696*** (0.07)	0.57*** (0.051)	0.015 (0.02)	0.016 (0.02)
Patient Age	0.001*** (0.0)	0.001*** (0.0)	0.0** (0.0)	-0.0 (0.0)
Trial	-0.035*** (0.01)	-0.029*** (0.007)	-0.002 (0.003)	-0.0 (0.003)
IV	0.333*** (0.013)	0.292*** (0.01)	0.016*** (0.004)	-0.002 (0.004)
CT with IV contrast	0.4*** (0.013)	0.253*** (0.01)	-0.013*** (0.004)	-0.000032
CT without IV contrast	0.283*** (0.013)	0.198*** (0.009)	-0.003 (0.004)	0.004 (0.004)
MRI	0.281*** (0.036)	0.245*** (0.026)	-0.027** (0.01)	0.011 (0.01)
Xray	0.202*** (0.011)	0.146*** (0.008)	-0.011*** (0.003)	-0.01** (0.003)
Ultrasound	0.25*** (0.016)	0.206*** (0.011)	-0.0 (0.004)	-0.004 (0.004)
Nurses on shift	-0.001 (0.002)	-0.000003	0.001 (0.001)	-0.0 (0.001)
MDs on shift	-0.028*** (0.006)	-0.023*** (0.004)	0.001 (0.002)	0.002 (0.002)
Current waiting count	0.005** (0.002)	0.014*** (0.001)	0.0 (0.0)	0.0 (0.0)

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Table EC.23 continued from previous page

Variable	**Log Time from Arrival to Disposition**	**Log Time from Arrival to ED Departure**	**ED Return within 72 Hours (with admission)**	**ED Return within 72 Hours (without admission)**
Current treatment count	0.005*** (0.001)	0.006*** (0.001)	-0.0 (0.0)	-0.0 (0.0)
Shift: 6 am-12 pm	0.188*** (0.024)	0.085*** (0.017)	-0.009 (0.007)	-0.006 (0.007)
Shift: 12 pm-6 pm	0.039 (0.033)	-0.015 (0.024)	-0.006 (0.009)	-0.01 (0.01)
Shift: 6 pm-12 am	-0.03 (0.029)	-0.063** (0.021)	-0.011 (0.008)	-0.003 (0.008)
ED Disposition Admit	-0.21*** (0.015)	0.138*** (0.011)	0.008. (0.004)	-0.024*** (0.004)
ED Disposition Hospital Observation	-0.001 (0.017)	0.234*** (0.012)	-0.005 (0.005)	-0.019*** (0.005)
ED Disposition Left Without Being Seen/AMA	-0.043 (0.069)	-0.005978	0.165*** (0.019)	0.035. (0.02)
ED Disposition Transfer to Health Care Facility	0.13** (0.047)	0.409*** (0.034)	-0.016 (0.013)	-0.023. (0.014)
Adjusted R^2	0.344	0.477	0.012	0.007
Sample size	11,015	11,015	11,015	11,015
F value	250.779	435.268	6.909	4.254

Table EC.23: No Matching: empirical model description for category C.

Variable	**Log Time from Arrival to Disposition**	**Log Time from Arrival to ED Departure**	**ED Return within 72 Hours (with admission)**	**ED Return within 72 Hours (without admission)**
Intercept	3.391*** (0.072)	4.026*** (0.053)	-0.006 (0.021)	0.024 (0.022)
ESI 1	0.384*** (0.091)	0.335*** (0.066)	0.028 (0.027)	0.038 (0.028)
ESI 2	0.967*** (0.067)	0.774*** (0.049)	0.026 (0.02)	0.019 (0.02)
ESI 3	0.979*** (0.066)	0.787*** (0.048)	0.02 (0.02)	0.02 (0.02)
ESI 4	0.69*** (0.067)	0.57*** (0.049)	0.015 (0.02)	0.015 (0.02)
Patient Age	0.001*** (0.0)	0.001*** (0.0)	0.0** (0.0)	-0.0 (0.0)
Trial	-0.042*** (0.01)	-0.035*** (0.007)	-0.002 (0.003)	-0.0 (0.003)
IV	0.344*** (0.013)	0.298*** (0.009)	0.017*** (0.004)	-0.002 (0.004)
CT with IV contrast	0.382*** (0.013)	0.244*** (0.009)	-0.013*** (0.004)	-0.000036
CT without IV contrast	0.273*** (0.012)	0.193*** (0.009)	-0.003 (0.004)	0.003 (0.004)
MRI	0.271*** (0.034)	0.234*** (0.025)	-0.027** (0.01)	0.011 (0.01)
Xray	0.185*** (0.01)	0.136*** (0.007)	-0.01*** (0.003)	-0.01** (0.003)
Ultrasound	0.239*** (0.015)	0.2*** (0.011)	0.0 (0.004)	-0.004 (0.005)
Nurses on shift	0.001 (0.002)	-0.000003	0.001 (0.001)	-0.0 (0.001)
MDs on shift	-0.027*** (0.006)	-0.023*** (0.004)	0.0 (0.002)	0.002 (0.002)
Current waiting count	0.004** (0.001)	0.014*** (0.001)	0.0 (0.0)	0.0 (0.0)

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Table EC.24 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Current treatment count	0.004*** (0.001)	0.006*** (0.001)	-0.0 (0.0)	-0.0 (0.0)
Shift: 6 am-12 pm	0.148*** (0.026)	0.053** (0.019)	-0.014. (0.008)	-0.005 (0.008)
Shift: 12 pm-6 pm	0.013 (0.033)	-0.036 (0.024)	-0.009 (0.01)	-0.011 (0.01)
Shift: 6 pm-12 am	-0.034 (0.029)	-0.072*** (0.021)	-0.012 (0.009)	-0.005 (0.009)
ED Disposition Admit	-0.214*** (0.014)	0.135*** (0.011)	0.008. (0.004)	-0.024*** (0.004)
ED Disposition Hospital Observation	-0.006 (0.016)	0.232*** (0.012)	-0.006 (0.005)	-0.019*** (0.005)
ED Disposition Left Without Being Seen/AMA	-0.023 (0.065)	-0.005232	0.164*** (0.019)	0.035. (0.02)
ED Disposition Transfer to Health Care Facility	0.138** (0.045)	0.415*** (0.033)	-0.017 (0.013)	-0.023. (0.014)
MD_A	0.139*** (0.023)	0.116*** (0.017)	-0.004 (0.007)	0.003 (0.007)
MD_AA	0.227*** (0.031)	0.259*** (0.023)	-0.012 (0.009)	-0.0002
MD_AB	0.211*** (0.034)	0.198*** (0.025)	0.006 (0.01)	0.004 (0.01)
MD_AC	0.353*** (0.037)	0.281*** (0.027)	-0.012 (0.011)	-0.018 (0.011)
MD_AD	-0.004085	-0.059. (0.031)	0.008 (0.013)	0.003 (0.013)
MD_AE	-0.051 (0.032)	0.001 (0.023)	0.006 (0.009)	-0.009 (0.01)
MD_AF	-0.003 (0.032)	0.027 (0.023)	-0.015 (0.01)	0.031** (0.01)
MD_AG	0.065. (0.039)	0.1*** (0.028)	-0.003 (0.011)	0.026* (0.012)
MD_AH	0.225*** (0.046)	0.207*** (0.034)	-0.001 (0.014)	-0.001 (0.014)
MD_AI	0.274*** (0.055)	0.174*** (0.04)	0.012 (0.016)	0.026 (0.017)
MD_AJ	0.194*** (0.032)	0.163*** (0.023)	0.007 (0.009)	-0.001 (0.01)
MD_AK	0.306*** (0.053)	0.253*** (0.039)	0.009 (0.016)	0.012 (0.016)
MD_B	0.304*** (0.024)	0.246*** (0.017)	-0.007 (0.007)	-0.001 (0.007)
MD_C	0.199*** (0.024)	0.155*** (0.018)	-0.006 (0.007)	-0.000112
MD_D	0.324*** (0.024)	0.238*** (0.018)	0.008 (0.007)	-0.003 (0.007)
MD_E	-0.174*** (0.024)	-0.023 (0.018)	-0.011 (0.007)	0.012. (0.007)
MD_F	0.009 (0.026)	0.054** (0.019)	0.003 (0.008)	0.002 (0.008)
MD_G	0.314*** (0.025)	0.252*** (0.018)	0.011 (0.007)	0.0 (0.008)
MD_H	0.165*** (0.025)	0.148*** (0.019)	-0.003 (0.008)	-0.003 (0.008)
MD_I	-0.142*** (0.026)	-0.052** (0.019)	0.004 (0.008)	-0.012 (0.008)
MD_J	-0.195*** (0.028)	-0.0008	0.003 (0.008)	0.007 (0.008)
MD_K	0.185*** (0.025)	0.147*** (0.018)	-0.009 (0.007)	-0.0 (0.008)
MD_L	0.092*** (0.025)	0.069*** (0.018)	0.007 (0.007)	0.001 (0.008)
MD_M	0.111*** (0.025)	0.103*** (0.019)	-0.000136	-0.006 (0.008)
MD_N	0.159*** (0.028)	0.164*** (0.02)	0.006 (0.008)	0.0 (0.009)
MD_O	0.134*** (0.026)	0.16*** (0.019)	0.001 (0.008)	0.0 (0.008)
MD_P	0.155*** (0.027)	0.151*** (0.02)	-0.006 (0.008)	-0.002 (0.008)
MD_Q	-0.285*** (0.027)	-0.001 (0.02)	0.018* (0.008)	-0.008 (0.008)
MD_R	-0.122*** (0.028)	-0.011 (0.021)	0.012 (0.008)	0.004 (0.009)
MD_S	0.209*** (0.029)	0.178*** (0.021)	-0.007 (0.008)	-0.005 (0.009)
MD_T	-0.181*** (0.033)	-0.102*** (0.024)	-0.006 (0.01)	-0.0 (0.01)
MD_U	-0.018 (0.03)	0.073** (0.022)	0.005 (0.009)	0.015 (0.009)
MD_V	0.279*** (0.032)	0.232*** (0.024)	-0.014 (0.01)	-0.019. (0.01)

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Table EC.24 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
MD_W	0.116*** (0.03)	0.095*** (0.022)	0.013 (0.009)	0.003 (0.009)
MD_X	-0.215*** (0.031)	-0.13*** (0.022)	0.004 (0.009)	0.002 (0.009)
MD_Y	0.194*** (0.031)	0.191*** (0.023)	0.002 (0.009)	-0.008 (0.009)
MD_Z	-0.00238	0.011 (0.025)	-0.016 (0.01)	0.006 (0.01)
Adjusted R^2	0.414	0.516	0.013	0.008
Sample size	11,015	11,015	11,015	11,015
F value	131.849	198.889	3.357	2.428

Table EC.24: No Matching: empirical model description for category B.

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	3.338*** (0.216)	4.138*** (0.157)	0.018 (0.061)	0.012 (0.067)
ESI 1	0.258 (0.238)	0.126 (0.173)	0.012 (0.067)	0.038 (0.074)
ESI 2	1.044*** (0.206)	0.672*** (0.15)	0.036 (0.058)	0.037 (0.064)
ESI 3	1.041*** (0.205)	0.659*** (0.15)	0.026 (0.058)	0.037 (0.064)
ESI 4	0.826*** (0.205)	0.493*** (0.15)	0.019 (0.058)	0.035 (0.064)
Patient Age	0.002*** (0.0)	0.001*** (0.0)	0.0 (0.0)	0.0 (0.0)
Trial	-0.057*** (0.014)	-0.047*** (0.01)	-0.003 (0.004)	0.002 (0.004)
IV	0.336*** (0.02)	0.292*** (0.015)	0.003 (0.006)	-0.01 (0.006)
CT with IV contrast	0.351*** (0.02)	0.228*** (0.014)	0.001 (0.006)	-0.001 (0.006)
CT without IV contrast	0.268*** (0.02)	0.186*** (0.015)	-0.0 (0.006)	0.004 (0.006)
MRI	0.255*** (0.051)	0.233*** (0.037)	-0.023 (0.015)	0.008 (0.016)
Xray	0.198*** (0.018)	0.155*** (0.013)	-0.013** (0.005)	0.003 (0.005)
Ultrasound	0.228*** (0.023)	0.203*** (0.016)	0.004 (0.006)	-0.007 (0.007)
Nurses on shift	-0.001 (0.003)	-0.003. (0.002)	0.002* (0.001)	-0.0 (0.001)
MDs on shift	-0.029*** (0.009)	-0.023*** (0.006)	-0.002 (0.002)	0.004 (0.003)
Current waiting count	0.005* (0.002)	0.015*** (0.002)	-0.0 (0.001)	0.001 (0.001)
Current treatment count	0.004*** (0.001)	0.005*** (0.001)	-0.001. (0.0)	-0.0 (0.0)
Shift: 12 pm-6 pm	0.03 (0.048)	-0.021 (0.035)	-0.001 (0.014)	-0.028. (0.015)
Shift: 6 am-12 pm	0.119** (0.037)	0.04 (0.027)	0.001 (0.011)	-0.019 (0.012)
Shift: 6 pm-12 am	-0.022 (0.041)	-0.00201	-0.003 (0.012)	-0.011 (0.013)
ED Disposition Admit	-0.209*** (0.022)	0.135*** (0.016)	0.013* (0.006)	-0.028*** (0.007)
ED Disposition Hospital Observation	-0.023 (0.024)	0.227*** (0.017)	0.004 (0.007)	-0.000112

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Table EC.25 continued from previous page

Variable	**Log Time from Arrival to Disposition**	**Log Time from Arrival to ED Departure**	**ED Return within 72 Hours (with admission)**	**ED Return within 72 Hours (without admission)**
ED Disposition Left Without Being Seen/AMA	-0.109 (0.1)	-0.013432	0.224*** (0.028)	0.043 (0.031)
ED Disposition Transfer to Health Care Facility	0.062 (0.067)	0.35*** (0.049)	-0.018 (0.019)	-0.035. (0.021)
MD_A	0.16*** (0.036)	0.132*** (0.026)	0.006 (0.01)	-0.003 (0.011)
MD_AA	0.128. (0.066)	0.218*** (0.048)	-0.011 (0.019)	-0.03 (0.021)
MD_AB	0.25*** (0.054)	0.207*** (0.04)	0.005 (0.015)	-0.001 (0.017)
MD_AC	0.314*** (0.049)	0.245*** (0.035)	-0.0 (0.014)	-0.016 (0.015)
MD_AD	-0.054 (0.053)	-0.02 (0.038)	0.017 (0.015)	0.01 (0.016)
MD_AE	-0.06 (0.044)	-0.002 (0.032)	0.005 (0.012)	-0.006 (0.014)
MD_AF	-0.043 (0.045)	-0.005 (0.033)	-0.025. (0.013)	0.042** (0.014)
MD_AG	0.055 (0.074)	0.088 (0.054)	0.006 (0.021)	0.025 (0.023)
MD_AH	0.258*** (0.063)	0.223*** (0.046)	-0.015 (0.018)	0.01 (0.02)
MD_AI	0.252*** (0.063)	0.158*** (0.046)	0.014 (0.018)	0.028 (0.02)
MD_AJ	0.18*** (0.043)	0.156*** (0.031)	0.008 (0.012)	-0.01 (0.013)
MD_AK	0.322*** (0.066)	0.273*** (0.048)	-0.004 (0.019)	0.029 (0.02)
MD_B	0.339*** (0.036)	0.27*** (0.026)	-0.008 (0.01)	0.007 (0.011)
MD_C	0.154*** (0.039)	0.137*** (0.028)	-0.002 (0.011)	-0.00036
MD_D	0.368*** (0.039)	0.258*** (0.028)	0.008 (0.011)	-0.013 (0.012)
MD_E	-0.153*** (0.033)	-0.013 (0.024)	-0.00018	0.027** (0.01)
MD_F	0.015 (0.042)	0.043 (0.03)	-0.005 (0.012)	-0.015 (0.013)
MD_G	0.311*** (0.038)	0.241*** (0.028)	0.005 (0.011)	-0.005 (0.012)
MD_H	0.154*** (0.041)	0.158*** (0.03)	0.016 (0.011)	0.009 (0.013)
MD_I	-0.105** (0.033)	-0.006 (0.024)	0.012 (0.009)	-0.009 (0.01)
MD_J	-0.183*** (0.04)	-0.035 (0.029)	-0.001 (0.011)	0.002 (0.012)
MD_K	0.184*** (0.035)	0.161*** (0.026)	-0.006 (0.01)	-0.003 (0.011)
MD_L	0.088** (0.034)	0.085*** (0.025)	0.014 (0.01)	-0.007 (0.011)
MD_M	0.134*** (0.037)	0.127*** (0.027)	-0.00021	-0.001 (0.011)
MD_N	0.204*** (0.052)	0.2*** (0.038)	-0.002 (0.015)	0.001 (0.016)
MD_O	0.206*** (0.044)	0.18*** (0.032)	-0.007 (0.012)	-0.016 (0.014)
MD_P	0.195*** (0.044)	0.179*** (0.032)	-0.009 (0.013)	-0.01 (0.014)
MD_Q	-0.303*** (0.036)	-0.001 (0.026)	0.019. (0.01)	-0.001 (0.011)
MD_R	-0.138** (0.044)	-0.032 (0.032)	-0.006 (0.013)	0.033* (0.014)
MD_S	0.196*** (0.039)	0.183*** (0.029)	0.0 (0.011)	-0.008 (0.012)
MD_T	-0.259*** (0.047)	-0.145*** (0.035)	0.017 (0.013)	-0.015 (0.015)
MD_U	-0.089 (0.055)	0.037 (0.04)	0.033* (0.015)	0.016 (0.017)
MD_V	0.39*** (0.068)	0.297*** (0.05)	-0.013 (0.019)	-0.014 (0.021)
MD_W	0.099* (0.041)	0.103*** (0.03)	0.015 (0.011)	-0.012 (0.013)
MD_X	-0.251*** (0.047)	-0.11** (0.034)	-0.008 (0.013)	0.01 (0.015)
MD_Y	0.168*** (0.044)	0.182*** (0.032)	-0.005 (0.012)	-0.008 (0.014)
MD_Z	-0.148*** (0.045)	-0.032 (0.033)	-0.016 (0.013)	-0.003 (0.014)
Abdominal Complaints	0.123 (0.082)	0.088 (0.06)	-0.001288	0.002 (0.025)
Abnormal Test Results	-0.037 (0.085)	0.046 (0.062)	-0.068** (0.024)	-0.006 (0.027)
Allergic Reaction	-0.103 (0.12)	-0.129 (0.087)	-0.037 (0.034)	-0.005 (0.037)
Back or Flank Pain	0.074 (0.085)	0.072 (0.062)	-0.03 (0.024)	-0.01 (0.027)

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Table EC.25 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Breast Complaints	-0.169 (0.261)	-0.151 (0.19)	-0.069 (0.074)	-0.039 (0.081)
Cardiac Arrhythmias	0.089 (0.092)	0.064 (0.067)	-0.068** (0.026)	-0.013 (0.029)
Chest Pain	0.084 (0.084)	0.035 (0.061)	-0.044. (0.024)	-0.014 (0.026)
Circulatory Issue	0.22 (0.361)	0.073 (0.263)	0.429*** (0.102)	-0.032 (0.112)
Dizziness/Lightheadedness/Syncope	0.111 (0.088)	0.073 (0.064)	-0.001575	-0.011 (0.027)
Ear Complaints	-0.028971	-0.015633	-0.002046	-0.015 (0.035)
Epistaxis	0.218. (0.121)	0.186* (0.088)	-0.00255	0.165*** (0.038)
Exposures, Bites, and Envenomations	-0.034125	-0.127 (0.091)	-0.063. (0.035)	-0.036 (0.039)
Extremity Complaints	-0.03 (0.083)	-0.016 (0.06)	-0.001173	-0.016 (0.026)
Eye Complaints	-0.109 (0.098)	-0.102 (0.071)	-0.001624	-0.009 (0.03)
Falls, Motor Vehicle Crashes, Assaults, and Trauma	0.063 (0.086)	0.061 (0.062)	-0.001368	-0.002 (0.027)
Fatigue and Weakness	-0.012 (0.089)	0.016 (0.065)	-0.042. (0.025)	0.002 (0.028)
Fevers, Sweats or Chills	-0.03 (0.09)	-0.001 (0.065)	-0.076** (0.025)	-0.013 (0.028)
Foreign Body	-0.19 (0.177)	-0.159 (0.129)	-0.06 (0.05)	-0.032 (0.055)
Gastrointestinal Issues	0.057 (0.084)	0.085 (0.061)	-0.001368	0.014 (0.026)
Genital Complaints	0.251** (0.095)	0.171* (0.069)	-0.001755	-0.018 (0.03)
Medical Device or Treatment Issue	0.077 (0.099)	0.143* (0.072)	-0.04 (0.028)	0.031 (0.031)
Medication Request	0.049 (0.3)	-0.055 (0.219)	-0.077 (0.085)	-0.052 (0.094)
Neurological Issue	0.01 (0.085)	0.035 (0.062)	-0.062** (0.024)	-0.009 (0.026)
Other Pain	-0.078 (0.091)	-0.031 (0.067)	-0.068** (0.026)	-0.009 (0.028)
Post-Op Issue	-0.108 (0.109)	-0.077 (0.079)	-0.002325	-0.029 (0.034)
Psychiatric Complaints	0.221. (0.123)	0.258** (0.09)	-0.062. (0.035)	0.003 (0.038)
Shortness of Breath	0.026 (0.084)	0.044 (0.062)	-0.037 (0.024)	0.004 (0.026)
Skin Complaints	-0.01547	-0.113. (0.062)	-0.0012	0.002 (0.027)
Substance Abuse Issues	0.072 (0.133)	0.001 (0.097)	-0.037 (0.038)	0.058 (0.041)
Upper Respiratory Symptoms	-0.064 (0.086)	-0.061 (0.063)	-0.041. (0.024)	-0.017 (0.027)
Urinary Complaints	0.078 (0.089)	0.13* (0.065)	-0.008 (0.025)	0.031 (0.028)
Adjusted R^2	0.436	0.533	0.025	0.015
Sample size	5158	5158	5158	5158
F value	45.329	66.48	2.469	1.864

Table EC.25: Matching on MD: empirical model description for category A.

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	3.297*** (0.207)	4.108*** (0.151)	-0.033 (0.058)	0.003 (0.064)
ESI 1	0.326 (0.238)	0.173 (0.174)	0.003 (0.067)	0.036 (0.074)
ESI 2	1.124*** (0.207)	0.741*** (0.151)	0.031 (0.058)	0.043 (0.064)
ESI 3	1.124*** (0.206)	0.73*** (0.151)	0.023 (0.058)	0.043 (0.064)
ESI 4	0.846*** (0.206)	0.516*** (0.151)	0.017 (0.058)	0.038 (0.064)
Patient Age	0.002*** (0.0)	0.001*** (0.0)	0.0. (0.0)	0.0 (0.0)
Trial	-0.053*** (0.014)	-0.043*** (0.01)	-0.002 (0.004)	0.002 (0.004)
IV	0.352*** (0.02)	0.305*** (0.014)	0.004 (0.005)	-0.009 (0.006)
CT with IV contrast	0.382*** (0.019)	0.243*** (0.014)	0.0 (0.005)	-0.001 (0.006)
CT without IV contrast	0.287*** (0.019)	0.201*** (0.014)	-0.001 (0.005)	0.002 (0.006)
MRI	0.233*** (0.051)	0.218*** (0.037)	-0.026. (0.014)	0.002 (0.016)
Xray	0.196*** (0.015)	0.141*** (0.011)	-0.012** (0.004)	-0.005 (0.005)
Ultrasound	0.245*** (0.022)	0.213*** (0.016)	0.003 (0.006)	-0.011 (0.007)
Nurses on shift	-0.001 (0.003)	-0.003 (0.002)	0.002** (0.001)	-0.0 (0.001)
MDs on shift	-0.03*** (0.009)	-0.024*** (0.006)	-0.002 (0.002)	0.004 (0.003)
Current waiting count	0.005* (0.003)	0.015*** (0.002)	-0.0 (0.001)	0.001 (0.001)
Current treatment count	0.004** (0.001)	0.005*** (0.001)	-0.001. (0.0)	-0.0 (0.0)
Shift: 12 pm-6 pm	0.027 (0.048)	-0.025 (0.035)	-0.002 (0.014)	-0.026. (0.015)
Shift: 6 am-12 pm	0.111** (0.038)	0.033 (0.028)	0.001 (0.011)	-0.019 (0.012)
Shift: 6 pm-12 am	-0.03 (0.042)	-0.00228	-0.004 (0.012)	-0.01 (0.013)
ED Disposition Admit	-0.228*** (0.022)	0.129*** (0.016)	0.014* (0.006)	-0.025*** (0.007)
ED Disposition Hospital Observation	-0.026 (0.024)	0.225*** (0.017)	0.003 (0.007)	-0.000119
ED Disposition Left Without Being Seen/AMA	-0.103 (0.101)	-0.013838	0.219*** (0.028)	0.041 (0.031)
ED Disposition Transfer to Health Care Facility	0.085 (0.067)	0.377*** (0.049)	-0.018 (0.019)	-0.029 (0.021)
MD_A	0.155*** (0.036)	0.127*** (0.026)	0.004 (0.01)	-0.003 (0.011)
MD_AA	0.141* (0.067)	0.225*** (0.049)	-0.014 (0.019)	-0.03 (0.021)
MD_AB	0.241*** (0.055)	0.205*** (0.04)	0.003 (0.015)	-0.002 (0.017)
MD_AC	0.305*** (0.049)	0.233*** (0.036)	-0.003 (0.014)	-0.019 (0.015)
MD_AD	-0.062 (0.053)	-0.031 (0.039)	0.018 (0.015)	0.007 (0.016)
MD_AE	-0.067 (0.044)	-0.009 (0.032)	0.008 (0.012)	-0.008 (0.014)
MD_AF	-0.052 (0.045)	-0.01 (0.033)	-0.025. (0.013)	0.041** (0.014)
MD_AG	0.036 (0.075)	0.075 (0.055)	0.002 (0.021)	0.024 (0.023)
MD_AH	0.257*** (0.064)	0.223*** (0.047)	-0.02 (0.018)	0.008 (0.02)
MD_AI	0.248*** (0.063)	0.153*** (0.046)	0.013 (0.018)	0.03 (0.02)
MD_AJ	0.185*** (0.043)	0.161*** (0.032)	0.006 (0.012)	-0.007 (0.013)
MD_AK	0.314*** (0.066)	0.27*** (0.048)	-0.004 (0.019)	0.03 (0.021)
MD_B	0.337*** (0.036)	0.269*** (0.027)	-0.01 (0.01)	0.006 (0.011)
MD_C	0.157*** (0.039)	0.136*** (0.028)	-0.004 (0.011)	-0.00036

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Table EC.26 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
MD_D	0.361*** (0.039)	0.255*** (0.028)	0.006 (0.011)	-0.012 (0.012)
MD_E	-0.167*** (0.033)	-0.022 (0.024)	-0.000189	0.027** (0.01)
MD_F	0.024 (0.042)	0.051. (0.031)	-0.006 (0.012)	-0.013 (0.013)
MD_G	0.316*** (0.039)	0.245*** (0.028)	0.004 (0.011)	-0.004 (0.012)
MD_H	0.159*** (0.041)	0.161*** (0.03)	0.014 (0.011)	0.008 (0.013)
MD_I	-0.102** (0.034)	-0.008 (0.024)	0.008 (0.009)	-0.012 (0.01)
MD_J	-0.186*** (0.04)	-0.035 (0.029)	-0.002 (0.011)	0.0 (0.012)
MD_K	0.183*** (0.035)	0.158*** (0.026)	-0.006 (0.01)	-0.003 (0.011)
MD_L	0.089** (0.034)	0.084*** (0.025)	0.012 (0.01)	-0.008 (0.011)
MD_M	0.137*** (0.037)	0.131*** (0.027)	-0.00021	-0.001 (0.011)
MD_N	0.197*** (0.053)	0.199*** (0.038)	-0.003 (0.015)	0.005 (0.016)
MD_O	0.205*** (0.044)	0.183*** (0.032)	-0.01 (0.012)	-0.016 (0.014)
MD_P	0.202*** (0.045)	0.187*** (0.033)	-0.011 (0.013)	-0.011 (0.014)
MD_Q	-0.305*** (0.036)	-0.001 (0.026)	0.017. (0.01)	-0.001 (0.011)
MD_R	-0.132** (0.045)	-0.033 (0.033)	-0.004 (0.013)	0.033* (0.014)
MD_S	0.195*** (0.039)	0.179*** (0.029)	-0.001 (0.011)	-0.011 (0.012)
MD_T	-0.261*** (0.048)	-0.152*** (0.035)	0.019 (0.013)	-0.016 (0.015)
MD_U	-0.087 (0.055)	0.035 (0.04)	0.03* (0.015)	0.018 (0.017)
MD_V	0.4*** (0.069)	0.317*** (0.05)	-0.013 (0.019)	-0.012 (0.021)
MD_W	0.096* (0.041)	0.1*** (0.03)	0.016 (0.011)	-0.014 (0.013)
MD_X	-0.243*** (0.048)	-0.104** (0.035)	-0.012 (0.013)	0.012 (0.015)
MD_Y	0.173*** (0.044)	0.189*** (0.032)	-0.007 (0.012)	-0.008 (0.014)
MD_Z	-0.154*** (0.045)	-0.037 (0.033)	-0.016 (0.013)	-0.003 (0.014)
Adjusted R^2	0.423	0.521	0.017	0.008
Sample size	5158	5158	5158	5158
F value	64.962	95.966	2.476	1.715

Table EC.26: Matching on MD: empirical model description for category B.

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	3.205*** (0.224)	4.086*** (0.16)	-0.024 (0.059)	0.005 (0.065)
ESI 1	0.486. (0.253)	0.258 (0.181)	0.001 (0.067)	0.021 (0.074)
ESI 2	1.202*** (0.22)	0.779*** (0.157)	0.03 (0.058)	0.037 (0.064)
ESI 3	1.237*** (0.219)	0.79*** (0.156)	0.021 (0.058)	0.035 (0.064)
ESI 4	0.943*** (0.219)	0.572*** (0.156)	0.014 (0.058)	0.03 (0.064)
Patient Age	0.002*** (0.0)	0.001*** (0.0)	0.0* (0.0)	0.0 (0.0)
Trial	-0.053*** (0.015)	-0.041*** (0.011)	-0.003 (0.004)	0.003 (0.004)
IV	0.342*** (0.02)	0.302*** (0.015)	0.003 (0.005)	-0.007 (0.006)
CT with IV contrast	0.401*** (0.02)	0.251*** (0.014)	0.0 (0.005)	-0.002 (0.006)
CT without IV contrast	0.302*** (0.02)	0.208*** (0.014)	-0.001 (0.005)	0.002 (0.006)

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Table EC.27 continued from previous page

Variable	**Log Time from Arrival to Disposition**	**Log Time from Arrival to ED Departure**	**ED Return within 72 Hours (with admission)**	**ED Return within 72 Hours (without admission)**
MRI	0.237*** (0.054)	0.224*** (0.038)	-0.026. (0.014)	0.003 (0.016)
Xray	0.213*** (0.016)	0.15*** (0.011)	-0.013** (0.004)	-0.005 (0.005)
Ultrasound	0.25*** (0.023)	0.214*** (0.016)	0.003 (0.006)	-0.009 (0.007)
Nurses on shift	-0.002 (0.003)	-0.003 (0.002)	0.002* (0.001)	-0.0 (0.001)
MDs on shift	-0.03** (0.009)	-0.024*** (0.007)	-0.002 (0.002)	0.003 (0.003)
Current waiting count	0.004. (0.003)	0.015*** (0.002)	0.0 (0.001)	0.001 (0.001)
Current treatment count	0.005*** (0.001)	0.005*** (0.001)	-0.001. (0.0)	-0.0 (0.0)
Shift: 12 pm-6 pm	0.07 (0.048)	0.013 (0.034)	-0.003 (0.013)	-0.024. (0.014)
Shift: 6 am-12 pm	0.185*** (0.033)	0.092*** (0.023)	-0.001 (0.009)	-0.00019
Shift: 6 pm-12 am	-0.006 (0.042)	-0.051. (0.03)	-0.007 (0.011)	-0.006 (0.012)
ED Disposition Admit	-0.218*** (0.023)	0.135*** (0.016)	0.014* (0.006)	-0.025*** (0.007)
ED Disposition Hospital Observation	-0.017 (0.025)	0.228*** (0.018)	0.003 (0.007)	-0.000126
ED Disposition Left Without Being Seen/AMA	-0.119 (0.107)	-0.015092	0.223*** (0.028)	0.045 (0.031)
ED Disposition Transfer to Health Care Facility	0.058 (0.071)	0.361*** (0.05)	-0.017 (0.019)	-0.03 (0.021)
Adjusted R^2	0.345	0.481	0.016	0.005
Sample size	5158	5158	5158	5158
F value	119.053	208.81	4.595	2.207

Table EC.27: Matching on MD: empirical model description for category C.

Variable	**Log Time from Arrival to Disposition**	**Log Time from Arrival to ED Departure**	**ED Return within 72 Hours (with admission)**	**ED Return within 72 Hours (without admission)**
Intercept	3.345*** (0.206)	4.13*** (0.152)	-0.004 (0.062)	-0.0 (0.068)
ESI 1	0.251 (0.231)	0.107 (0.17)	-0.004 (0.069)	0.036 (0.076)
ESI 2	1.039*** (0.2)	0.659*** (0.147)	0.024 (0.06)	0.044 (0.066)
ESI 3	1.069*** (0.2)	0.672*** (0.147)	0.012 (0.06)	0.046 (0.065)
ESI 4	0.846*** (0.2)	0.513*** (0.147)	0.007 (0.06)	0.037 (0.065)
Patient Age	0.002*** (0.0)	0.002*** (0.0)	0.0* (0.0)	0.0 (0.0)
Trial	-0.057*** (0.013)	-0.045*** (0.009)	0.0 (0.004)	0.002 (0.004)
IV	0.321*** (0.018)	0.284*** (0.013)	0.018*** (0.005)	-0.005 (0.006)
CT with IV contrast	0.361*** (0.017)	0.235*** (0.013)	-0.000065	-0.006 (0.006)
CT without IV contrast	0.244*** (0.018)	0.174*** (0.013)	0.0 (0.005)	0.007 (0.006)

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Table EC.28 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
MRI	0.282*** (0.048)	0.253*** (0.035)	-0.000448	0.012 (0.016)
Xray	0.196*** (0.016)	0.159*** (0.012)	-0.000055	-0.009. (0.005)
Ultrasound	0.223*** (0.02)	0.199*** (0.015)	-0.006 (0.006)	-0.002 (0.007)
Nurses on shift	0.003 (0.002)	-0.002 (0.002)	0.001 (0.001)	-0.0 (0.001)
MDs on shift	-0.035*** (0.008)	-0.025*** (0.006)	0.001 (0.002)	0.001 (0.003)
Current waiting count	0.001 (0.002)	0.013*** (0.002)	0.0 (0.001)	0.0 (0.001)
Current treatment count	0.004*** (0.001)	0.005*** (0.001)	-0.001. (0.0)	-0.0 (0.0)
Shift: 12 pm-6 pm	0.029 (0.043)	-0.018 (0.032)	-0.006 (0.013)	-0.007 (0.014)
Shift: 6 am-12 pm	0.143*** (0.033)	0.056* (0.024)	-0.014 (0.01)	-0.003 (0.011)
Shift: 6 pm-12 am	-0.02 (0.037)	-0.047. (0.027)	-0.007 (0.011)	-0.002 (0.012)
ED Disposition Admit	-0.201*** (0.019)	0.128*** (0.014)	0.013* (0.006)	-0.028*** (0.006)
ED Disposition Hospital Observation	-0.009 (0.021)	0.233*** (0.016)	-0.002 (0.006)	-0.022** (0.007)
ED Disposition Left Without Being Seen/AMA	-0.15. (0.088)	-0.226*** (0.064)	0.143*** (0.026)	0.031 (0.029)
ED Disposition Transfer to Health Care Facility	0.112. (0.061)	0.416*** (0.045)	-0.023 (0.018)	-0.035. (0.02)
MD_A	0.165*** (0.031)	0.137*** (0.023)	-0.007 (0.009)	0.015 (0.01)
MD_AA	0.268*** (0.041)	0.287*** (0.03)	-0.014 (0.012)	-0.026. (0.014)
MD_AB	0.238*** (0.043)	0.222*** (0.032)	-0.0 (0.013)	0.014 (0.014)
MD_AC	0.317*** (0.048)	0.28*** (0.035)	-0.008 (0.014)	-0.000496
MD_AD	-0.008083	-0.066 (0.043)	0.025 (0.018)	-0.002 (0.019)
MD_AE	-0.051 (0.041)	-0.007 (0.03)	0.003 (0.012)	-0.011 (0.013)
MD_AF	-0.053 (0.04)	0.002 (0.029)	-0.017 (0.012)	0.041** (0.013)
MD_AG	0.06 (0.05)	0.101** (0.037)	0.002 (0.015)	0.027. (0.016)
MD_AH	0.215*** (0.062)	0.183*** (0.046)	-0.014 (0.019)	0.021 (0.02)
MD_AI	0.296*** (0.066)	0.201*** (0.048)	-0.008 (0.02)	0.028 (0.022)
MD_AJ	0.189*** (0.042)	0.144*** (0.031)	-0.017 (0.013)	0.001 (0.014)
MD_AK	0.312*** (0.07)	0.246*** (0.052)	0.038. (0.021)	0.014 (0.023)
MD_B	0.278*** (0.032)	0.212*** (0.024)	-0.011 (0.01)	-0.008 (0.011)
MD_C	0.183*** (0.032)	0.147*** (0.024)	-0.006 (0.01)	-0.02. (0.011)
MD_D	0.288*** (0.032)	0.213*** (0.024)	-0.0 (0.01)	-0.016 (0.011)
MD_E	-0.18*** (0.032)	-0.03 (0.024)	-0.01 (0.01)	0.013 (0.011)
MD_F	-0.002 (0.034)	0.068** (0.025)	0.008 (0.01)	0.003 (0.011)
MD_G	0.285*** (0.032)	0.239*** (0.023)	-0.004 (0.01)	-0.007 (0.01)
MD_H	0.171*** (0.035)	0.175*** (0.026)	-0.005 (0.011)	-0.002 (0.012)
MD_I	-0.124*** (0.035)	-0.046. (0.025)	0.023* (0.01)	-0.016 (0.011)
MD_J	-0.183*** (0.038)	-0.023 (0.028)	0.008 (0.011)	0.002 (0.012)
MD_K	0.201*** (0.034)	0.169*** (0.025)	-0.018. (0.01)	-0.004 (0.011)
MD_L	0.079* (0.034)	0.04 (0.025)	0.009 (0.01)	0.005 (0.011)
MD_M	0.075* (0.034)	0.078** (0.025)	-0.014 (0.01)	0.001 (0.011)
MD_N	0.19*** (0.039)	0.18*** (0.029)	0.007 (0.012)	-0.01 (0.013)
MD_O	0.133*** (0.034)	0.154*** (0.025)	-0.007 (0.01)	0.005 (0.011)

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Table EC.28 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
MD_P	0.181*** (0.037)	0.172*** (0.027)	0.0 (0.011)	-0.012 (0.012)
MD_Q	-0.337*** (0.036)	-0.033 (0.026)	0.012 (0.011)	-0.019 (0.012)
MD_R	-0.123*** (0.037)	-0.021 (0.027)	0.017 (0.011)	0.011 (0.012)
MD_S	0.19*** (0.038)	0.178*** (0.028)	-0.003 (0.011)	-0.013 (0.012)
MD_T	-0.129** (0.046)	-0.061. (0.034)	-0.0 (0.014)	-0.012 (0.015)
MD_U	-0.029 (0.04)	0.075* (0.029)	0.007 (0.012)	0.025. (0.013)
MD_V	0.271*** (0.048)	0.238*** (0.035)	-0.024. (0.014)	-0.016 (0.016)
MD_W	0.123** (0.039)	0.12*** (0.028)	0.015 (0.012)	-0.004 (0.013)
MD_X	-0.148*** (0.044)	-0.002432	0.022. (0.013)	0.009 (0.014)
MD_Y	0.208*** (0.041)	0.226*** (0.03)	0.0 (0.012)	-0.012 (0.014)
MD_Z	-0.074. (0.043)	0.005 (0.032)	-0.015 (0.013)	0.006 (0.014)
Abdominal Complaints	-0.009 (0.069)	-0.003 (0.051)	0.004 (0.021)	-0.0 (0.023)
Abnormal Test Results	-0.122. (0.074)	-0.034 (0.054)	-0.021 (0.022)	0.007 (0.024)
Allergic Reaction	-0.203. (0.107)	-0.012168	0.003 (0.032)	-0.001 (0.035)
Back or Flank Pain	-0.03 (0.073)	-0.0 (0.053)	0.03 (0.022)	-0.009 (0.024)
Breast Complaints	-0.12 (0.287)	-0.074 (0.212)	-0.012 (0.086)	-0.042 (0.094)
Cardiac Arrhythmias	0.03 (0.084)	0.017 (0.062)	-0.022 (0.025)	0.01 (0.027)
Chest Pain	-0.002 (0.071)	-0.026 (0.053)	0.002 (0.021)	0.0 (0.023)
Circulatory Issue	-0.274 (0.252)	-0.11 (0.185)	0.484*** (0.076)	-0.018 (0.082)
Dizziness/Lightheadedness/Syncope	-0.025 (0.077)	-0.033 (0.057)	-0.016 (0.023)	-0.025 (0.025)
Ear Complaints	-0.395*** (0.099)	-0.247*** (0.073)	-0.008 (0.03)	-0.01 (0.032)
Epistaxis	0.059 (0.11)	0.079 (0.081)	-0.019 (0.033)	0.146*** (0.036)
Exposures, Bites, and Envenomations	-0.42*** (0.118)	-0.229** (0.087)	0.026 (0.036)	-0.027 (0.039)
Extremity Complaints	-0.010792	-0.005668	-0.0 (0.021)	0.001 (0.023)
Eye Complaints	0.017 (0.099)	0.015 (0.073)	-0.018 (0.03)	-0.008 (0.032)
Falls, Motor Vehicle Crashes, Assaults, and Trauma	-0.065 (0.075)	-0.036 (0.055)	-0.004 (0.022)	0.006 (0.024)
Fatigue and Weakness	-0.1 (0.085)	-0.074 (0.062)	-0.014 (0.025)	-0.004 (0.028)
Fevers, Sweats or Chills	-0.129 (0.085)	-0.082 (0.063)	-0.017 (0.026)	-0.001 (0.028)
Foreign Body	-0.459** (0.168)	-0.331** (0.124)	-0.001 (0.051)	-0.023 (0.055)
Gastrointestinal Issues	-0.059 (0.071)	0.004 (0.053)	-0.007 (0.021)	0.015 (0.023)
Genital Complaints	0.067 (0.091)	0.039 (0.067)	0.003 (0.027)	-0.031 (0.03)
Medical Device or Treatment Issue	-0.113 (0.097)	-0.018 (0.072)	0.047 (0.029)	0.04 (0.032)
Medication Request	-0.447. (0.252)	-0.082398	-0.01 (0.076)	-0.045 (0.083)
Neurological Issue	-0.073 (0.072)	-0.036 (0.053)	-0.001 (0.022)	0.004 (0.024)
Other Pain	-0.154. (0.086)	-0.113. (0.063)	0.007 (0.026)	0.017 (0.028)
Post-Op Issue	-0.021715	-0.132. (0.075)	0.001 (0.03)	0.003 (0.033)

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Table EC.28 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Psychiatric Complaints	0.322** (0.109)	0.285*** (0.08)	-0.016 (0.033)	0.002 (0.036)
Shortness of Breath	-0.073 (0.072)	-0.019 (0.053)	-0.001 (0.022)	0.002 (0.024)
Skin Complaints	-0.263*** (0.075)	-0.158** (0.055)	-0.002 (0.022)	0.006 (0.024)
Substance Abuse Issues	0.073 (0.109)	0.01 (0.08)	-0.008 (0.033)	0.032 (0.036)
Upper Respiratory Symptoms	-0.0129	-0.007535	0.008 (0.023)	-0.014 (0.025)
Urinary Complaints	0.017 (0.077)	0.062 (0.057)	0.029 (0.023)	0.035 (0.025)
Adjusted R^2	0.419	0.513	0.022	0.014
Sample size	5976	5976	5976	5976
F value	48.881	70.948	2.479	1.915

Table EC.28: Matching on CC: empirical model description for category A.

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	3.212*** (0.2)	4.046*** (0.147)	-0.003 (0.06)	-0.005 (0.065)
ESI 1	0.347 (0.232)	0.163 (0.17)	-0.009 (0.069)	0.04 (0.075)
ESI 2	1.136*** (0.201)	0.726*** (0.148)	0.022 (0.06)	0.051 (0.065)
ESI 3	1.152*** (0.2)	0.73*** (0.147)	0.014 (0.06)	0.051 (0.065)
ESI 4	0.856*** (0.201)	0.52*** (0.148)	0.011 (0.06)	0.043 (0.065)
Patient Age	0.002*** (0.0)	0.002*** (0.0)	0.0* (0.0)	0.0 (0.0)
Trial	-0.057*** (0.013)	-0.045*** (0.009)	0.0 (0.004)	0.002 (0.004)
IV	0.335*** (0.017)	0.296*** (0.013)	0.02*** (0.005)	-0.006 (0.006)
CT with IV contrast	0.384*** (0.017)	0.245*** (0.012)	-0.00006	-0.009 (0.005)
CT without IV contrast	0.257*** (0.017)	0.183*** (0.012)	0.002 (0.005)	0.004 (0.005)
MRI	0.266*** (0.048)	0.24*** (0.035)	-0.028. (0.014)	0.01 (0.015)
Xray	0.188*** (0.014)	0.141*** (0.01)	-0.014*** (0.004)	-0.013** (0.004)
Ultrasound	0.224*** (0.019)	0.195*** (0.014)	-0.005 (0.006)	-0.005 (0.006)
Nurses on shift	0.003 (0.002)	-0.002 (0.002)	0.001 (0.001)	-0.0 (0.001)
MDs on shift	-0.035*** (0.008)	-0.026*** (0.006)	0.001 (0.002)	0.0 (0.003)
Current waiting count	0.002 (0.002)	0.014*** (0.002)	0.0 (0.001)	0.0 (0.001)
Current treatment count	0.004*** (0.001)	0.005*** (0.001)	-0.001 (0.0)	-0.0 (0.0)
Shift: 12 pm-6 pm	0.028 (0.044)	-0.02 (0.032)	-0.008 (0.013)	-0.007 (0.014)
Shift: 6 am-12 pm	0.139*** (0.034)	0.053* (0.025)	-0.016 (0.01)	-0.003 (0.011)
Shift: 6 pm-12 am	-0.02 (0.038)	-0.049. (0.028)	-0.01 (0.011)	-0.002 (0.012)

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Table EC.29 continued from previous page

Variable	**Log Time from Arrival to Disposition**	**Log Time from Arrival to ED Departure**	**ED Return within 72 Hours (with admission)**	**ED Return within 72 Hours (without admission)**
ED Disposition Admit	-0.216*** (0.019)	0.125*** (0.014)	0.011. (0.006)	-0.027*** (0.006)
ED Disposition Hospital Observation	-0.013 (0.022)	0.229*** (0.016)	-0.002 (0.006)	-0.022** (0.007)
ED Disposition Left Without Being Seen/AMA	-0.156. (0.088)	-0.23*** (0.065)	0.138*** (0.026)	0.031 (0.029)
ED Disposition Transfer to Health Care Facility	0.146* (0.061)	0.449*** (0.045)	-0.025 (0.018)	-0.034. (0.02)
MD_A	0.159*** (0.031)	0.131*** (0.023)	-0.008 (0.009)	0.012 (0.01)
MD_AA	0.261*** (0.042)	0.28*** (0.031)	-0.013 (0.012)	-0.000406
MD_AB	0.234*** (0.044)	0.222*** (0.032)	0.001 (0.013)	0.013 (0.014)
MD_AC	0.313*** (0.048)	0.277*** (0.035)	-0.009 (0.014)	-0.000496
MD_AD	-0.008909	-0.072. (0.044)	0.026 (0.018)	-0.002 (0.019)
MD_AE	-0.058 (0.041)	-0.016 (0.03)	0.005 (0.012)	-0.015 (0.013)
MD_AF	-0.064 (0.04)	-0.005 (0.029)	-0.016 (0.012)	0.04** (0.013)
MD_AG	0.041 (0.05)	0.089* (0.037)	0.002 (0.015)	0.027 (0.016)
MD_AH	0.215*** (0.063)	0.183*** (0.046)	-0.017 (0.019)	0.021 (0.02)
MD_AI	0.292*** (0.066)	0.196*** (0.049)	-0.009 (0.02)	0.03 (0.022)
MD_AJ	0.198*** (0.042)	0.15*** (0.031)	-0.015 (0.013)	0.004 (0.014)
MD_AK	0.308*** (0.071)	0.25*** (0.052)	0.037. (0.021)	0.016 (0.023)
MD_B	0.275*** (0.033)	0.212*** (0.024)	-0.009 (0.01)	-0.008 (0.011)
MD_C	0.18*** (0.033)	0.142*** (0.024)	-0.007 (0.01)	-0.000231
MD_D	0.287*** (0.032)	0.216*** (0.024)	0.0 (0.01)	-0.016 (0.011)
MD_E	-0.188*** (0.032)	-0.033 (0.024)	-0.009 (0.01)	0.015 (0.011)
MD_F	-0.005 (0.034)	0.065** (0.025)	0.008 (0.01)	0.003 (0.011)
MD_G	0.282*** (0.032)	0.238*** (0.024)	-0.004 (0.01)	-0.006 (0.01)
MD_H	0.165*** (0.035)	0.171*** (0.026)	-0.006 (0.011)	-0.002 (0.012)
MD_I	-0.126*** (0.035)	-0.047. (0.026)	0.022* (0.01)	-0.017 (0.011)
MD_J	-0.189*** (0.038)	-0.026 (0.028)	0.008 (0.011)	0.002 (0.012)
MD_K	0.2*** (0.034)	0.166*** (0.025)	-0.015 (0.01)	-0.006 (0.011)
MD_L	0.074* (0.035)	0.037 (0.025)	0.01 (0.01)	0.005 (0.011)
MD_M	0.074* (0.035)	0.078** (0.025)	-0.013 (0.01)	0.001 (0.011)
MD_N	0.183*** (0.039)	0.178*** (0.029)	0.005 (0.012)	-0.01 (0.013)
MD_O	0.132*** (0.034)	0.156*** (0.025)	-0.008 (0.01)	0.007 (0.011)
MD_P	0.177*** (0.038)	0.17*** (0.028)	-0.0 (0.011)	-0.013 (0.012)
MD_Q	-0.342*** (0.036)	-0.038 (0.027)	0.01 (0.011)	-0.019. (0.012)
MD_R	-0.128*** (0.037)	-0.025 (0.027)	0.017 (0.011)	0.011 (0.012)
MD_S	0.185*** (0.038)	0.171*** (0.028)	-0.001 (0.011)	-0.016 (0.012)
MD_T	-0.134** (0.046)	-0.002312	0.002 (0.014)	-0.013 (0.015)
MD_U	-0.017 (0.04)	0.08** (0.029)	0.007 (0.012)	0.027* (0.013)
MD_V	0.259*** (0.049)	0.232*** (0.036)	-0.024. (0.014)	-0.017 (0.016)
MD_W	0.113** (0.039)	0.113*** (0.029)	0.016 (0.012)	-0.005 (0.013)
MD_X	-0.137** (0.044)	-0.002277	0.02 (0.013)	0.011 (0.014)
MD_Y	0.21*** (0.042)	0.229*** (0.031)	-0.001 (0.012)	-0.013 (0.014)
MD_Z	-0.065 (0.043)	0.012 (0.032)	-0.015 (0.013)	0.007 (0.014)

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Table EC.29 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Adjusted R^2	0.405	0.502	0.012	0.01
Sample size	5976	5976	5976	5976
F value	70.024	103.162	2.267	1.975

Table EC.29: Matching on CC: empirical model description for category B.

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	3.158*** (0.215)	4.059*** (0.156)	-0.003 (0.061)	-0.004 (0.066)
ESI 1	0.491* (0.244)	0.236 (0.176)	-0.009 (0.069)	0.03 (0.075)
ESI 2	1.253*** (0.212)	0.791*** (0.153)	0.022 (0.06)	0.045 (0.065)
ESI 3	1.269*** (0.211)	0.795*** (0.153)	0.014 (0.06)	0.045 (0.065)
ESI 4	0.972*** (0.212)	0.586*** (0.153)	0.011 (0.06)	0.037 (0.065)
Patient Age	0.002*** (0.0)	0.002*** (0.0)	0.0* (0.0)	0.0 (0.0)
Trial	-0.047*** (0.013)	-0.039*** (0.01)	-0.001 (0.004)	0.002 (0.004)
IV	0.332*** (0.018)	0.295*** (0.013)	0.018*** (0.005)	-0.006 (0.006)
CT with IV contrast	0.401*** (0.017)	0.254*** (0.013)	-0.013** (0.005)	-0.008 (0.005)
CT without IV contrast	0.269*** (0.018)	0.188*** (0.013)	0.001 (0.005)	0.005 (0.005)
MRI	0.267*** (0.05)	0.247*** (0.036)	-0.000392	0.011 (0.015)
Xray	0.201*** (0.014)	0.148*** (0.01)	-0.015*** (0.004)	-0.012** (0.004)
Ultrasound	0.225*** (0.02)	0.196*** (0.015)	-0.006 (0.006)	-0.004 (0.006)
Nurses on shift	0.001 (0.003)	-0.003 (0.002)	0.001 (0.001)	0.0 (0.001)
MDs on shift	-0.032*** (0.008)	-0.024*** (0.006)	0.001 (0.002)	0.001 (0.003)
Current waiting count	0.003 (0.002)	0.014*** (0.002)	0.0 (0.001)	0.0 (0.001)
Current treatment count	0.004*** (0.001)	0.005*** (0.001)	-0.001. (0.0)	-0.0 (0.0)
Shift: 12 pm-6 pm	0.05 (0.044)	-0.001 (0.032)	-0.009 (0.013)	-0.004 (0.014)
Shift: 6 am-12 pm	0.177*** (0.031)	0.082*** (0.023)	-0.014 (0.009)	-0.003 (0.01)
Shift: 6 pm-12 am	-0.013 (0.039)	-0.038 (0.028)	-0.011 (0.011)	0.002 (0.012)
ED Disposition Admit	-0.208*** (0.02)	0.131*** (0.015)	0.011. (0.006)	-0.026*** (0.006)
ED Disposition Hospital Observation	-0.009 (0.023)	0.232*** (0.016)	-0.002 (0.006)	-0.021** (0.007)
ED Disposition Left Without Being Seen/AMA	-0.158. (0.093)	-0.229*** (0.067)	0.14*** (0.026)	0.029 (0.029)

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Table EC.30 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
ED Disposition Transfer to Health Care Facility	0.114. (0.064)	0.43*** (0.046)	-0.022 (0.018)	-0.033. (0.02)
Adjusted R^2	0.336	0.464	0.012	0.006
Sample size	5976	5976	5976	5976
F value	132.687	225.586	4.199	2.674

Table EC.30: Matching on CC: empirical model description for category C.

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	2.944*** (0.081)	3.544*** (0.059)	0.029 (0.026)	0.084*** (0.025)
ESI 1	0.212* (0.104)	0.229** (0.075)	0.081* (0.033)	-0.027 (0.032)
ESI 2	0.78*** (0.079)	0.686*** (0.057)	0.031 (0.025)	-0.014 (0.024)
ESI 3	0.764*** (0.078)	0.682*** (0.057)	0.015 (0.025)	-0.015 (0.024)
ESI 4	0.516*** (0.079)	0.496*** (0.057)	0.01 (0.025)	-0.017 (0.024)
Patient Age	0.002*** (0.0)	0.002*** (0.0)	0.0 (0.0)	0
Trial	-0.00024 (0.0)	-0.027*** (0.007)	-0.009 (0.003)	-0.001 (0.003)
IV	0.322*** (0.013)	0.28*** (0.01)	0.027*** (0.004)	-0.002 (0.004)
CT with IV contrast	0.356*** (0.013)	0.227*** (0.01)	-0.02*** (0.004)	-0.011** (0.004)
CT without IV contrast	0.261*** (0.014)	0.177*** (0.01)	-0.00004	-0.008. (0.004)
MRI	0.315*** (0.035)	0.269*** (0.026)	-0.000297	-0.006 (0.011)
Xray	0.187*** (0.012)	0.145*** (0.009)	-0.01** (0.004)	-0.007. (0.004)
Ultrasound	0.196*** (0.015)	0.17*** (0.011)	-0.003 (0.005)	0.005 (0.005)
Nurses on shift	0.001 (0.002)	-0.000003	0.0 (0.001)	-0.001. (0.001)
MDs on shift	-0.023*** (0.006)	-0.018*** (0.004)	0.002 (0.002)	0.004* (0.002)
Current waiting count	0.003* (0.002)	0.013*** (0.001)	0.0 (0.0)	0.001 (0.0)
Current treatment count	0.004*** (0.001)	0.005*** (0.001)	-0.0 (0.0)	-0.0. (0.0)
Shift: 12 pm-6 pm	0.019 (0.033)	-0.032 (0.024)	-0.003 (0.011)	0.004 (0.01)
Shift: 6 am-12 pm	0.152*** (0.025)	0.063*** (0.018)	-0.014. (0.008)	0.001 (0.008)
Shift: 6 pm-12 am	-0.037 (0.029)	-0.059** (0.021)	-0.017. (0.009)	0.015. (0.009)
ED Disposition Admit	0.393*** (0.024)	0.696*** (0.017)	-0.014. (0.008)	0.007 (0.007)
ED Disposition Discharge	0.593*** (0.022)	0.559*** (0.016)	-0.000119	0.028*** (0.007)
ED Disposition Hospital Observation	0.585*** (0.024)	0.807*** (0.018)	-0.029*** (0.008)	0.016* (0.008)

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Table EC.31 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
ED Disposition Left Without Being Seen/AMA	0.662*** (0.054)	0.536*** (0.039)	0.135*** (0.017)	0.039* (0.017)
ED Disposition Transfer to Health Care Facility	0.711*** (0.046)	0.946*** (0.034)	-0.046** (0.015)	-0.006 (0.014)
MD_A	0.164*** (0.025)	0.134*** (0.018)	-0.014. (0.008)	0.02* (0.008)
MD_AA	0.236*** (0.03)	0.242*** (0.022)	-0.015 (0.01)	-0.017. (0.009)
MD_AB	0.211*** (0.034)	0.17*** (0.024)	-0.004 (0.011)	0.009 (0.01)
MD_AC	0.375*** (0.037)	0.285*** (0.027)	-0.013 (0.012)	-0.000253
MD_AD	-0.006318	-0.054 (0.039)	-0.004 (0.017)	-0.021 (0.017)
MD_AE	-0.087** (0.029)	-0.036. (0.021)	0.0 (0.009)	-0.004 (0.009)
MD_AF	0.004 (0.03)	0.008 (0.021)	-0.017. (0.009)	0.03** (0.009)
MD_AG	0.031 (0.04)	0.074* (0.029)	0.025* (0.013)	0.001 (0.012)
MD_AH	0.25*** (0.059)	0.248*** (0.043)	-0.02 (0.019)	-0.011 (0.018)
MD_AI	0.27*** (0.065)	0.192*** (0.047)	0.027 (0.021)	0.032 (0.02)
MD_AJ	0.171*** (0.025)	0.136*** (0.018)	0.041*** (0.008)	-0.007 (0.008)
MD_AK	0.408*** (0.048)	0.311*** (0.034)	0.02 (0.015)	-0.001 (0.015)
MD_B	0.298*** (0.024)	0.228*** (0.017)	0.011 (0.008)	-0.002 (0.007)
MD_C	0.199*** (0.025)	0.158*** (0.018)	-0.011 (0.008)	-0.011 (0.008)
MD_D	0.327*** (0.024)	0.231*** (0.018)	0.002 (0.008)	-0.006 (0.008)
MD_E	-0.181*** (0.023)	-0.000629	-0.000105	0.014. (0.007)
MD_F	0.04 (0.028)	0.067*** (0.02)	0.015. (0.009)	0.004 (0.009)
MD_G	0.306*** (0.024)	0.235*** (0.017)	0.016* (0.008)	0.006 (0.007)
MD_H	0.133*** (0.025)	0.117*** (0.018)	0.007 (0.008)	0.014. (0.008)
MD_I	-0.172*** (0.028)	-0.062** (0.02)	0.013 (0.009)	-0.009 (0.009)
MD_J	-0.206*** (0.03)	-0.064** (0.022)	-0.003 (0.01)	0.01 (0.009)
MD_K	0.156*** (0.025)	0.121*** (0.018)	0.001 (0.008)	0.007 (0.008)
MD_L	0.073** (0.026)	0.041* (0.019)	0.002 (0.008)	0.017* (0.008)
MD_M	0.082*** (0.025)	0.092*** (0.018)	-0.013 (0.008)	-0.003 (0.008)
MD_N	0.122*** (0.031)	0.14*** (0.022)	0.018. (0.01)	0.003 (0.01)
MD_O	0.144*** (0.025)	0.159*** (0.018)	-0.01 (0.008)	-0.002 (0.008)
MD_P	0.107*** (0.027)	0.117*** (0.019)	-0.011 (0.009)	-0.006 (0.008)
MD_Q	-0.298*** (0.026)	-0.012 (0.019)	0.004 (0.008)	0.028*** (0.008)
MD_R	-0.145*** (0.029)	-0.003 (0.021)	0.003 (0.009)	0.012 (0.009)
MD_S	0.201*** (0.029)	0.158*** (0.021)	-0.008 (0.009)	-0.006 (0.009)
MD_T	-0.208*** (0.042)	-0.128*** (0.03)	-0.021 (0.013)	-0.004 (0.013)
MD_U	-0.0021	0.036 (0.022)	0.0 (0.01)	0.012 (0.009)
MD_V	0.251*** (0.036)	0.205*** (0.026)	-0.03** (0.011)	-0.013 (0.011)
MD_W	0.102*** (0.029)	0.09*** (0.021)	0.021* (0.009)	0.016. (0.009)
MD_X	-0.286*** (0.03)	-0.196*** (0.022)	-0.002 (0.01)	-0.008 (0.009)
MD_Y	0.151*** (0.03)	0.145*** (0.022)	0.001 (0.01)	-0.008 (0.009)
MD_Z	-0.101** (0.033)	-0.004 (0.024)	0.012 (0.01)	0.009 (0.01)
Abdominal Complaints	0.088 (0.054)	0.046 (0.039)	0.001 (0.017)	-0.047** (0.017)
Abnormal Test Results	-0.057 (0.057)	0.022 (0.041)	-0.017 (0.018)	-0.048** (0.018)
Allergic Reaction	-0.09 (0.091)	-0.098 (0.066)	-0.019 (0.029)	-0.088** (0.028)
Back or Flank Pain	0.121* (0.057)	0.073. (0.041)	0.004 (0.018)	-0.055** (0.018)

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Table EC.31 continued from previous page

Variable	**Log Time from Arrival to Disposition**	**Log Time from Arrival to ED Departure**	**ED Return within 72 Hours (with admission)**	**ED Return within 72 Hours (without admission)**
Breast Complaints	-0.143 (0.183)	-0.069 (0.133)	-0.028 (0.058)	-0.075 (0.057)
Cardiac Arrhythmias	-0.012 (0.061)	-0.055 (0.044)	-0.036. (0.019)	-0.064*** (0.019)
Chest Pain	0.085 (0.056)	0.023 (0.041)	0.008 (0.018)	-0.053** (0.017)
Circulatory Issue	-0.038 (0.175)	-0.141 (0.127)	-0.001 (0.056)	-0.071 (0.054)
Dizziness/ Lightheadedness/ Syncope	0.126* (0.058)	0.053 (0.042)	-0.027 (0.018)	-0.064*** (0.018)
Ear Complaints	-0.376*** (0.091)	-0.275*** (0.066)	-0.03 (0.029)	-0.001764
Epistaxis	0.061 (0.081)	0.038 (0.059)	-0.035 (0.026)	0.066** (0.025)
Exposures, Bites, and Envenomations	-0.313*** (0.092)	-0.234*** (0.067)	0.025 (0.029)	-0.086** (0.029)
Extremity Complaints	-0.036 (0.055)	-0.039 (0.04)	-0.015 (0.018)	-0.055** (0.017)
Eye Complaints	-0.235*** (0.063)	-0.167*** (0.046)	-0.025 (0.02)	-0.0008
Falls, Motor Vehicle Crashes, Assaults, and Trauma	0.004 (0.057)	-0.002 (0.041)	-0.014 (0.018)	-0.029. (0.018)
Fatigue and Weakness	0.01 (0.059)	0.007 (0.043)	-0.006 (0.019)	-0.049** (0.018)
Fevers, Sweats or Chills	-0.093 (0.06)	-0.058 (0.044)	-0.031 (0.019)	-0.064*** (0.019)
Foreign Body	-0.27. (0.139)	-0.024442	-0.015 (0.044)	-0.081. (0.043)
Gastrointestinal Issues	0.032 (0.056)	0.046 (0.04)	-0.017 (0.018)	-0.048** (0.017)
Genital Complaints	0.225*** (0.066)	0.135** (0.048)	-0.031 (0.021)	-0.00092
Medical Device or Treatment Issue	0.057 (0.068)	0.075 (0.049)	-0.002 (0.022)	-0.028 (0.021)
Medication Request	-0.853*** (0.125)	-0.308*** (0.09)	-0.026 (0.04)	0.041 (0.039)
Neurological Issue	0.0 (0.057)	0.004 (0.041)	-0.024 (0.018)	-0.031. (0.017)
Other Pain	-0.029 (0.063)	0.004 (0.046)	-0.012 (0.02)	-0.06** (0.02)
Post-Op Issue	-0.117 (0.076)	-0.00781	-0.008 (0.024)	-0.077** (0.024)
Psychiatric Complaints	0.303*** (0.088)	0.24*** (0.064)	-0.013 (0.028)	-0.039 (0.027)
Shortness of Breath	-0.006 (0.056)	0.01 (0.041)	-0.021 (0.018)	-0.056** (0.017)
Skin Complaints	-0.165** (0.057)	-0.132** (0.041)	-0.014 (0.018)	-0.048** (0.018)
Substance Abuse Issues	0.13 (0.083)	0.023 (0.06)	-0.001378	-0.046. (0.026)
Upper Respiratory Symptoms	-0.066 (0.058)	-0.074. (0.042)	-0.004 (0.019)	-0.06*** (0.018)
Urinary Complaints	0.046 (0.06)	0.073. (0.043)	0.027 (0.019)	-0.029 (0.018)
Adjusted R^2	0.438	0.533	0.026	0.019
Sample size	10926	10926	10926	10926
F value	95.582	139.762	4.273	3.323

Table EC.31: Propensity Score Matching: empirical model description for category A.

Variable	**Log Time from Arrival to Disposition**	**Log Time from Arrival to ED Departure**	**ED Return within 72 Hours (with admission)**	**ED Return within 72 Hours (without admission)**
Intercept	2.766*** (0.068)	3.44*** (0.049)	0.02 (0.021)	0.05* (0.021)
ESI 1	0.464*** (0.101)	0.364*** (0.073)	0.073* (0.032)	-0.028 (0.031)
ESI 2	1.034*** (0.075)	0.827*** (0.054)	0.03 (0.024)	-0.021 (0.023)
ESI 3	1.022*** (0.074)	0.827*** (0.054)	0.019 (0.023)	-0.022 (0.023)
ESI 4	0.72*** (0.075)	0.601*** (0.054)	0.012 (0.023)	-0.025 (0.023)
Patient Age	0.002*** (0.0)	0.002*** (0.0)	0.0 (0.0)	0
Trial	-0.00022 (0.0)	-0.026*** (0.007)	-0.009 (0.003)	-0.001 (0.003)
IV	0.342*** (0.013)	0.294*** (0.009)	0.027*** (0.004)	-0.004 (0.004)
CT with IV contrast	0.383*** (0.013)	0.241*** (0.009)	-0.016*** (0.004)	-0.011** (0.004)
CT without IV contrast	0.289*** (0.013)	0.197*** (0.009)	-0.000036	-0.004 (0.004)
MRI	0.297*** (0.035)	0.253*** (0.025)	-0.031** (0.011)	-0.003 (0.011)
Xray	0.185*** (0.01)	0.135*** (0.007)	-0.011** (0.003)	-0.012*** (0.003)
Ultrasound	0.211*** (0.015)	0.179*** (0.011)	-0.004 (0.005)	0.003 (0.004)
Nurses on shift	-0.0 (0.002)	-0.000003	0.0 (0.001)	-0.001 (0.001)
MDs on shift	-0.025*** (0.006)	-0.019*** (0.004)	0.002 (0.002)	0.004* (0.002)
Current waiting count	0.003* (0.002)	0.013*** (0.001)	-0.0 (0.0)	0.001 (0.0)
Current treatment count	0.005*** (0.001)	0.005*** (0.001)	-0.0 (0.0)	-0.0. (0.0)
Shift: 12 pm-6 pm	0.009 (0.034)	-0.041. (0.024)	-0.005 (0.011)	0.005 (0.01)
Shift: 6 am-12 pm	0.139*** (0.025)	0.054** (0.018)	-0.000128	0.003 (0.008)
Shift: 6 pm-12 am	-0.054. (0.029)	-0.072*** (0.021)	-0.000162	0.015. (0.009)
ED Disposition Admit	0.334*** (0.022)	0.667*** (0.016)	-0.000112	0.0 (0.007)
ED Disposition Discharge	0.556*** (0.02)	0.535*** (0.014)	-0.018** (0.006)	0.021*** (0.006)
ED Disposition Hospital Observation	0.546*** (0.023)	0.782*** (0.016)	-0.031*** (0.007)	0.008 (0.007)
ED Disposition Left Without Being Seen/AMA	0.644*** (0.054)	0.518*** (0.039)	0.134*** (0.017)	0.029. (0.016)
ED Disposition Transfer to Health Care Facility	0.687*** (0.046)	0.937*** (0.033)	-0.05*** (0.014)	-0.009 (0.014)
MD_A	0.16*** (0.026)	0.134*** (0.019)	-0.015. (0.008)	0.019* (0.008)
MD_AA	0.233*** (0.03)	0.24*** (0.022)	-0.016. (0.01)	-0.000171
MD_AB	0.211*** (0.034)	0.176*** (0.025)	-0.003 (0.011)	0.01 (0.01)
MD_AC	0.36*** (0.038)	0.272*** (0.027)	-0.015 (0.012)	-0.000276
MD_AD	-0.00638	-0.057 (0.04)	-0.003 (0.017)	-0.023 (0.017)
MD_AE	-0.104*** (0.029)	-0.001008	-0.0 (0.009)	-0.007 (0.009)
MD_AF	-0.006 (0.03)	0.005 (0.022)	-0.000171	0.029** (0.009)
MD_AG	0.026 (0.041)	0.071* (0.029)	0.024. (0.013)	0.001 (0.012)
MD_AH	0.254*** (0.06)	0.252*** (0.043)	-0.021 (0.019)	-0.011 (0.018)
MD_AI	0.269*** (0.065)	0.187*** (0.047)	0.03 (0.021)	0.03 (0.02)
MD_AJ	0.17*** (0.025)	0.133*** (0.018)	0.041*** (0.008)	-0.006 (0.008)
MD_AK	0.407*** (0.048)	0.308*** (0.035)	0.019 (0.015)	-0.003 (0.015)

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Table EC.32 continued from previous page

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
MD_B	0.299*** (0.024)	0.23*** (0.017)	0.011 (0.008)	-0.002 (0.007)
MD_C	0.195*** (0.025)	0.154*** (0.018)	-0.012 (0.008)	-0.013 (0.008)
MD_D	0.322*** (0.025)	0.232*** (0.018)	0.003 (0.008)	-0.005 (0.008)
MD_E	-0.208*** (0.024)	-0.05** (0.017)	-0.000105	0.015* (0.007)
MD_F	0.043 (0.028)	0.068*** (0.02)	0.016. (0.009)	0.002 (0.009)
MD_G	0.302*** (0.024)	0.234*** (0.017)	0.016* (0.008)	0.005 (0.007)
MD_H	0.134*** (0.025)	0.117*** (0.018)	0.005 (0.008)	0.014. (0.008)
MD_I	-0.176*** (0.028)	-0.061** (0.02)	0.012 (0.009)	-0.012 (0.009)
MD_J	-0.219*** (0.03)	-0.07** (0.022)	-0.004 (0.01)	0.009 (0.009)
MD_K	0.16*** (0.025)	0.122*** (0.018)	0.002 (0.008)	0.004 (0.008)
MD_L	0.065* (0.026)	0.037. (0.019)	0.003 (0.008)	0.016* (0.008)
MD_M	0.073** (0.025)	0.085*** (0.018)	-0.013. (0.008)	-0.004 (0.008)
MD_N	0.116*** (0.031)	0.14*** (0.023)	0.017. (0.01)	0.004 (0.01)
MD_O	0.13*** (0.025)	0.151*** (0.018)	-0.01 (0.008)	-0.001 (0.008)
MD_P	0.102*** (0.027)	0.113*** (0.02)	-0.012 (0.009)	-0.006 (0.008)
MD_Q	-0.308*** (0.027)	-0.016 (0.019)	0.004 (0.008)	0.028*** (0.008)
MD_R	-0.154*** (0.029)	-0.012 (0.021)	0.002 (0.009)	0.008 (0.009)
MD_S	0.194*** (0.029)	0.149*** (0.021)	-0.006 (0.009)	-0.009 (0.009)
MD_T	-0.216*** (0.042)	-0.136*** (0.03)	-0.019 (0.013)	-0.006 (0.013)
MD_U	-0.00222	0.035 (0.022)	-0.0 (0.009)	0.012 (0.009)
MD_V	0.268*** (0.036)	0.218*** (0.026)	-0.031** (0.011)	-0.013 (0.011)
MD_W	0.09** (0.029)	0.082*** (0.021)	0.022* (0.009)	0.014 (0.009)
MD_X	-0.286*** (0.031)	-0.198*** (0.022)	-0.005 (0.01)	-0.008 (0.009)
MD_Y	0.161*** (0.031)	0.153*** (0.022)	0.002 (0.01)	-0.008 (0.009)
MD_Z	-0.11*** (0.033)	-0.012 (0.024)	0.01 (0.01)	0.009 (0.01)
Adjusted R^2	0.42	0.52	0.022	0.012
Sample size	10926	10926	10926	10926
F value	134.895	201.962	5.129	3.305

Table EC.32: Propensity Score Matching: empirical model description for category B.

Variable	Log Time from Arrival to Disposition	Log Time from Arrival to ED Departure	ED Return within 72 Hours (with admission)	ED Return within 72 Hours (without admission)
Intercept	2.822*** (0.072)	3.497*** (0.051)	0.019 (0.021)	0.045* (0.021)
ESI 1	0.467*** (0.107)	0.373*** (0.076)	0.074* (0.032)	-0.026 (0.031)
ESI 2	1.032*** (0.08)	0.831*** (0.057)	0.031 (0.024)	-0.022 (0.023)
ESI 3	1.019*** (0.079)	0.831*** (0.056)	0.02 (0.023)	-0.022 (0.023)
ESI 4	0.725*** (0.079)	0.607*** (0.056)	0.014 (0.023)	-0.024 (0.023)
Patient Age	0.002*** (0.0)	0.001*** (0.0)	0.0 (0.0)	0
Trial	-0.00022 (0.0)	-0.026*** (0.007)	-0.009 (0.003)	-0.001 (0.003)
IV	0.33*** (0.014)	0.286*** (0.01)	0.026*** (0.004)	-0.004 (0.004)
CT with IV contrast	0.401*** (0.014)	0.25*** (0.01)	-0.015*** (0.004)	-0.011** (0.004)

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Table EC.33 continued from previous page

Variable	**Log Time from Arrival to Disposition**	**Log Time from Arrival to ED Departure**	**ED Return within 72 Hours (with admission)**	**ED Return within 72 Hours (without admission)**
CT without IV contrast	0.303*** (0.013)	0.203*** (0.009)	-0.007. (0.004)	-0.004 (0.004)
MRI	0.286*** (0.037)	0.258*** (0.026)	-0.033** (0.011)	-0.003 (0.011)
Xray	0.206*** (0.011)	0.146*** (0.008)	-0.012*** (0.003)	-0.012*** (0.003)
Ultrasound	0.221*** (0.016)	0.186*** (0.011)	-0.003 (0.005)	0.003 (0.004)
Nurses on shift	-0.002 (0.002)	-0.004** (0.001)	0.0 (0.001)	-0.001 (0.001)
MDs on shift	-0.025*** (0.006)	-0.018*** (0.005)	0.002 (0.002)	0.004* (0.002)
Current waiting count	0.004* (0.002)	0.013*** (0.001)	-0.0 (0.0)	0.001 (0.0)
Current treatment count	0.005*** (0.001)	0.006*** (0.001)	-0.0 (0.0)	0
Shift: 12 pm-6 pm	0.035 (0.035)	-0.026 (0.024)	-0.004 (0.01)	0.007 (0.01)
Shift: 6 am-12 pm	0.184*** (0.024)	0.082*** (0.017)	-0.012. (0.007)	0.004 (0.007)
Shift: 6 pm-12 am	-0.052. (0.03)	-0.067** (0.021)	-0.00018	0.017* (0.009)
ED Disposition Admit	0.348*** (0.023)	0.682*** (0.016)	-0.000112	-0.002 (0.007)
ED Disposition Discharge	0.562*** (0.021)	0.545*** (0.015)	-0.019** (0.006)	0.02*** (0.006)
ED Disposition Hospital Observation	0.566*** (0.024)	0.799*** (0.017)	-0.029*** (0.007)	0.007 (0.007)
ED Disposition Left Without Being Seen/AMA	0.653*** (0.057)	0.53*** (0.04)	0.133*** (0.017)	0.028. (0.016)
ED Disposition Transfer to Health Care Facility	0.692*** (0.048)	0.941*** (0.034)	-0.05*** (0.014)	-0.008 (0.014)
Adjusted R^2	0.344	0.478	0.017	0.009
Sample size	10926	10926	10926	10926
F value	250.151	435.76	9.125	5.467

Table EC.33: Propensity Score Matching: empirical model description for category C.

EC.7.3. Bonferroni Correction

We evaluated the robustness of our findings concerning the independence of our outcome variables. A violation of this assumption could lead to an increased likelihood of Type I errors, where null hypotheses are incorrectly rejected. This risk is heightened when multiple comparisons are made across different outcomes. To address this potential issue, we initially conducted a correlation analysis to examine the interdependence among our outcome variables. We found a significant correlation between time from arrival to disposition and time from arrival to ED departure, which is expected since time from arrival to disposition is always part of the total time a patient spends in the ED.

To further ensure the robustness of our results against potential correlations among all outcome variables, we employed a highly conservative approach using the Bonferroni correction. This adjustment modifies the significance threshold, requiring p-values to be less than 0.025 (0.05 divided by 2 outcome variables) to be considered significant. Applying this stringent criterion, we continued to observe significant results across all models presented in Tables 5-6 and Tables EC.15-EC.16 with the exception of the models pertaining to propensity score matching for the outcome variable “log time from arrival to disposition.” These additional analyses reinforce the validity of our empirical findings.