Estimating ICU Bed Levels to Prevent Over-Capacity: An Agent-Based Model

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1 Introduction

More than five million patients are admitted to U.S. Intensive Care Units (ICUs) each year for treatments and interventions for acute and life-critical conditions.

ICU stays represent 13.2% of all hospital costs [1] and hospital stays that involve ICU services are 2.5 more costly than other hospital stays [2], whilst also carrying the highest mortality of any hospital unit [3]. For these reasons, the study of ICU medicine is of great interest to enable both improvement in clinical outcomes and more efficient health resource utilisation.

1.1 Problem Statement and Motivations

The availability of Intensive Care Unit (hereafter ICU) beds is important in determining a critically ill patient's clinical outcome. The delay of admission from the emergency room and other, non-ICU wards to the ICU increase a patient's mortality risk [4] [5] [6]. The primary purpose of this paper is to demonstrate bed numbers that would be required to meet demand at different confidence levels and thereby prevent such delays. It is hoped that this approach will support hospital resource management and planning at the hospital-level.

Central to the issue of capacity is the tradeoff associated with specialisation- that is, whether a hospital should adapt its ICU beds to provide more specialised care at the risk that these beds become less well-suited to treat other patients. Specialised ICU beds were shown to provide no length of stay or mortality benefit compared to generalised ICU beds in a study of 84,182 patients in 124 ICUs [7]. Additionally, critically ill patients assigned to an open bed in a different subspecialty ICU- the practise of 'boarding', even when they are treated by the same care team, saw increased mortality [8]. This evidence suggests that improved patient outcomes should not be a rationale for specialisation, although there may be other valid reasons such as resource management. Despite this, as hospital size increases, hospitals the prevalence of specialised ICU units increases [9]. The secondary purpose of this repo is to provide a quantification of numbers of beds that would be required to prevent 'boarding' in specialised ICUs in one hospital through simulation. We hope these simulations will support decision-making with regards to the tradeoffs of specialisation of ICUs and general ICU management.

Finally, we aim to show how sensitive our results are to changes in patient admission patterns. Seasonal patterns in ICU admission and mortality are well documented [10] [11], notably in countries with harsh winter climates and/or influenza seasons. Situations in which over-capacity arises may result in higher overall inpatient cost [12] and increased boarding (associated with worse patient outcomes.) Here, we are especially interested in unpredictable admissions pattern changes. We expect that changes in patient admission patterns to have a significant impact on specialised ICU bed requirements to meet the same confidence level for not reaching ICU capacity.

1.2 Agent-Based Model

To support these aims, we built an Agent-Based Model (ABM) using hospital Length Of Stay (hereafter LOS) estimates and patient admission distributions drawn from the MIMIC-III critical care database. MIMIC-III is a large, freely-available database comprising de-identified health-related data associated with over 40,000 patients who stayed in critical care units of the Beth Israel Deaconess Medical Center (BIDMC) between 2001 and 2012. This database is well-suited to the task due to its detailed patient characteristics and treatment information allowing prediction of length of stay and admission time records which allow the estimation of patient admission distributions.

To achieve the best length of stay estimations, we experimented with multiple machine learning techniques and present the results here. As part of that investigation, we include findings on feature importances and correlations, notably sepsis. Additionally, we use parametric methods to estimate patient admission distributions and then update these methods using Bayesian techniques in order to be able to capture changing priors relating to admissions. These components come together

in the final Agent-Based Model, which we designed to best simulate the hospital admissions, flow and discharge processes.

1.3 Main results

To ensure that no ICU runs over capacity at the 95% confidence level, 16, 12, 31, 45, 16 and 16 beds would be required in the Coronary Care Unit (CCU), Cardiac Surgery Recovery Unit (CSRU), Neonatal ICU (NICU), Medical ICU (MICU), Trauma/Surgical ICU (TSICU) and Surgical ICU (SICU) respectively. This totals 105 adult beds and 31 infant beds in the whole hospital that would be required to prevent boarding, which is 36% and 55% more than the hospital runs currently (105/77, 31/20.)

A simulated prolonged heat wave increased the number of beds required to prevent boarding at the 95% confidence level by 4.7% for adult ICUs and 9.7% for infant beds. 17, 13, 34, 47, 17 and 18 beds would be required under a scenario of heat for the CCU, CSRU, NICU, MICU, TSICU and SICU respectively. These results show that relatively small changes in admission patterns can have an effect on ICU and hospital capacity requirements.

The sensitivity of our results to changes in admissions distributions highlight the circumstances to which our bed estimates can and cannot be extended. This demonstrates that our results are hospital, context-specific, such that recommendations for bed numbers at BIDMC cannot be directly translated to recommendations at other hospitals. In order to purpose recommendations for other hospitals, further research into how admissions distributions generalise across populations would be required. For example, how admission patterns are different in areas with different demographic, ethnic compositions, migrations, hospital openings or closures.

Despite these limitations, we believe that this approach could be used by the BIDMC to support decisions about ICU bed resource allocation and additionally to any other hospital which has patient admission records available for distribution estimation. Specifically, the number of beds required per ICU to ensure capacity is not reached and also as part of a broader hospital resource allocation study to determine the tradeoffs associated with specialisation of ICU beds and under/over-utilisation of ICU resources.

2 Data

2.1 Data Sources

The data in this study is derived from four sources: the freely-available MIMIC-III database, the Barcelona GSE Data Science Center, the MIMIC-Extract open-source pipeline for pre-processing electronic health record data contained in the MIMIC-III database [13], and the Agency for Healthcare Research and Quality (AHRQ) [14]. Connecting data from these sources allow us to construct specific probability distributions for patient admissions, ICU boarding, and sepsis, which will parameterise the distributions from which we draw in our Agent-Based Model. The data extracted from each source is summarized in Figure 1.

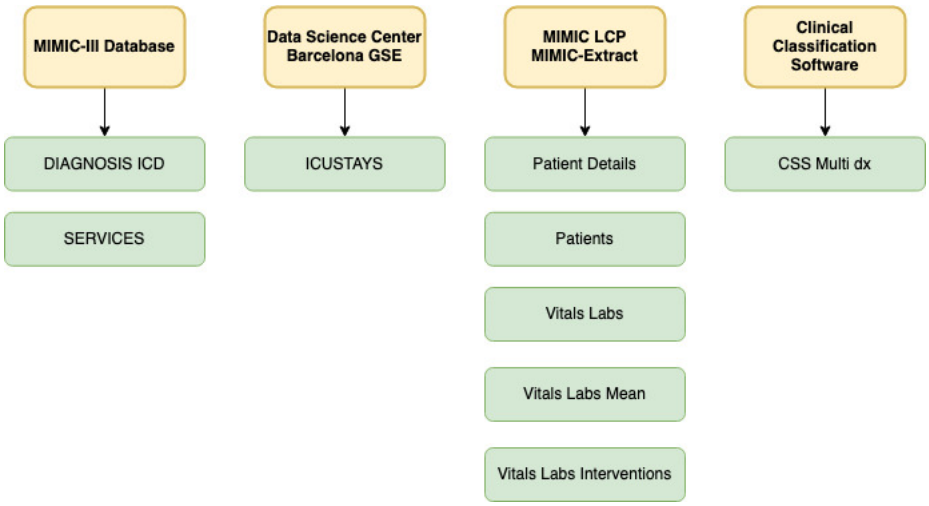


Figure 1: Raw Data Sources

The data used to construct these probability distributions is prepared by combining the 'DIAGNOSIS_ICD', 'ICUSTAYS' and 'SERVICES' tables from MIMIC-III, with a modified version of the 'ICUSTAYS' table provided by Barcelona GSE Data Science Center based on previous work to backshift the anonymised dates (to reverse the impacts of anonymisation by shifting the dates back into a realistic timeframe.) The result is a dataset of 61532 rows with a time period of admission dates between 2000-12-31 and 2012-12-29 (4381 days).

However, these backshifted dates do not match the date range and the number of days that we expect to be available in the MIMIC-III database (based on dates when information was written to the database), which is between 1 June 2001 to 10 October 2012 (4147 days). This is because the correction process is imperfect. In light of this, we choose to normalize our distributions using the number of days recorded in the MIMIC-III dataset instead of the Data Science Center's date range.

We also utilise the Clinical Classification Software (CCS) that categorises International Classification of Diseases (ICD)-9 codes. This table was developed by the Agency for Healthcare Research and Quality (AHRQ) in order to extract patient diagnoses at a level of detailed granularity. These alphanumeric ICD-9 codes are between three to five digits long. Digits 1–3 reveal categorical information and digits 4–5 reveal more granular information relating to etiology, such as anatomic site or manifestations. This relevant for our estimation of proportion of patients admitted to each specialised ICU, and whether a patient was admitted to their ideal ICU or not (an indication of whether boarding is taking place).

We also follow MIMIC-Extract's data processing method for standardized unit conversion, outlier detection, aggregating semantically equivalent features, and preserving the time series nature of clinical data. These characteristics are essential for making machine learning predictions regarding sepsis in the Agent-Based Model.

Specifically, we create four tables that include both static and time series features, 'patients', 'vitals labs', 'vitals labs mean', and 'interventions'. The workflow in MIMIC-Extract is summarized in 2, which demonstrates that SQL query results from the MIMIC relational database are processed to generate four output tables, which maintain the time series nature of clinical data and also provide an aggregated featurization of the cohort selected. The process only considers patients with at least 30 hours of data available and extracts the first 24 hours of the data. The 6 hour gap time is to prevent temporal label leakage.

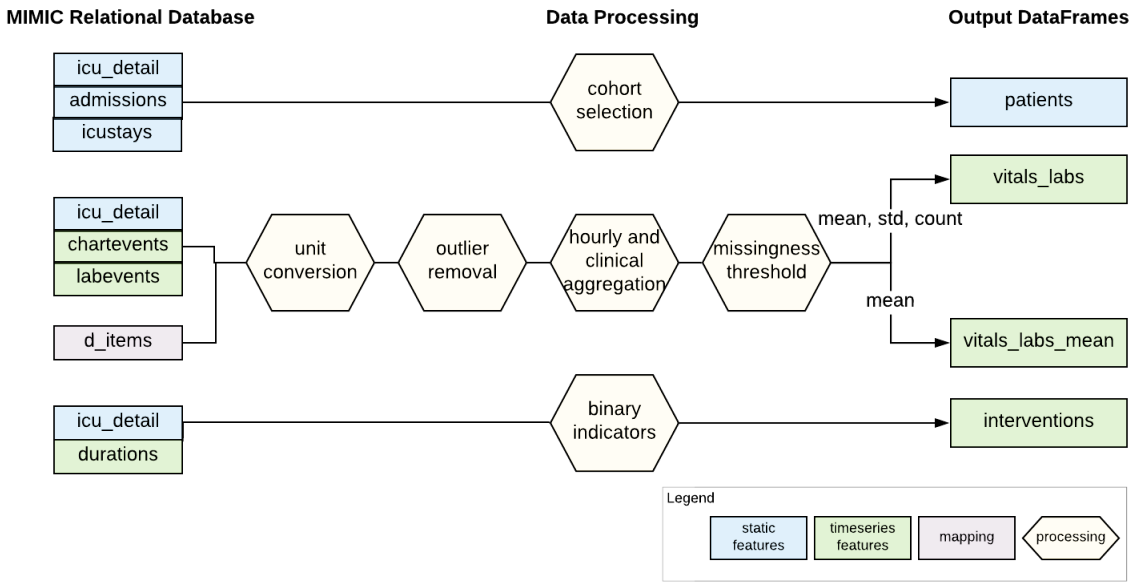


Figure 2: MIMIC-Extract Workflow (Source: MIMIC-Extract)

We extract 30 static variables (listed in Appendix 2) and 93 Time-varying Vitals and Labs (listed in Appendix B).

2.2 Data Splits

In order to avoid data leakage in our prediction models, we split our dataset into 20% for clustering exploration and 80% for LOS training, testing, and validation. We also use the 80% data split to generate the admissions probability distributions that are applied in the Agent-Based Model.

Compared to the adult ICUs, we observe approximately 50% less data for the NICU. Our dataset does not have information for NICU patients after the date 31 August 2007. We manage this issue when creating admission distributions by normalising the NICU data by a date range of 2001-06-01 to 2007-08-31, which represents 2282 days.

2.3 NICU Admissions Estimation

Within our dataset of 3591 days, we observe missing observations for the NICU after 1700 days. This represents a subset of missing data from 2008-2012. In comparison to the other ICUs, for which we have available data between 2003-2012, the roughly 50% reduction in data may result in an incomplete representation of NICU admissions in our Agent-Based Model.

To ensure that we accurately model the probability of patient admissions to the NICU without any distortion for the missing data, we generate an informative prior distribution using the shorter period between 2003-2007, and apply a bias towards the probability of zero admissions. We believe

that this is a realistic representation of the admission patterns for the NICU, based on the fact that the Beth Israel Hospital introduced a protocol to stop early elective deliveries in 2008 which can be seen in Figure 3. We recognize that the successful reduction in early term deliveries directly influences NICU admissions, and therefore our method prevents the Agent-Based Model from using outdated information regarding NICU admissions from this hospital.

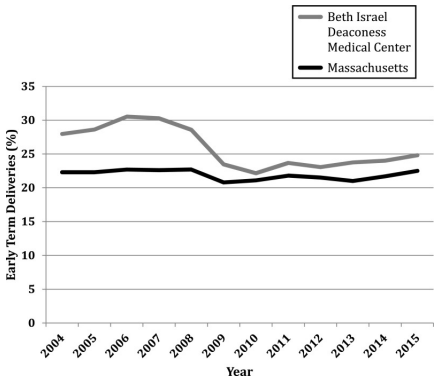


Figure 3: BIDMC of Boston

Following the above transformations, the NICU priors no longer incorporate zero admissions during the period of missing data, and do not exhibit a prior shift. A simulation of the Bayes updated admission distributions is shown in Figure 4.

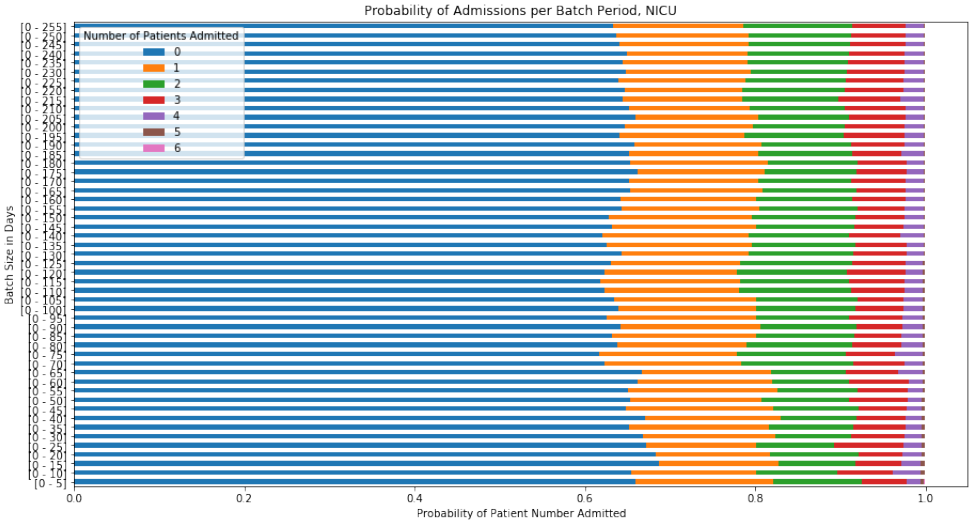


Figure 4: Final Prior Distribution for NICU

3 Setup of the Agent-Based Simulations

In general, ABM is a 'bottom-up' systems modelling approach from which emerging properties arise from the interaction of constituent parts. In this study, these agents and interactions are set up in a way that simulates processes and produces outcome measurements (bed numbers) that support the objectives laid out in the introduction. Those design choices are justified in this section. An overview of the Agent-Based Model Design can be found in Figure 5.

3.1 Agents

BIDMC's ICU system was modelled with the agents being individual patients, assigned characteristics of ideal ICU unit, actual ICU unit (if ideal unit is over capacity), cluster indicating distinct length of stay distribution and sepsis flag.

Each cluster indicates a distinct length of stay distribution from which to draw Length Of Stay (Hereafter LOS.) The purpose of the cluster is to enable representative LOS distribution dynamics to be incorporated into the ABM whilst at the same time maintaining data buckets that are large enough to allow sensible estimation of patient admission distributions (see section 4.3.2: The Curse of Dimensionality for full discussion on sparsity of admission distributions). It is this design choice which determines the level of granularity of the ABM i.e. the sub-populations dynamics present. For our purposes, including additional patient features only made sense if that feature created new sub-populations with different behaviours i.e. different length of stay distributions between the groups created. A detailed discussion of how clusters were identified using machine learning, and a comparison to performance in the literature, is included in section 4.5: ICU LOS prediction.

3.2 Patient flow through the ICU

The 6 ICUs are modelled independently, with no transfer of patients between ICUs when the 'ideal' ICU is over capacity. As our primary interest is the number of beds that would be required in each ICU to prevent over-capacity, this step is important to ensure that no steps are taken to reduce capacity estimates through intervention.

Patient origin (e.g. elective, emergency) is disregarded as all patients contribute to capacity equally. For the same reason, no distinction is made between patients exiting the ICU to enter another ward, leave the hospital or in the case of death; these outcomes have the same impact on bed availability. These could be valid extensions of our methodology, where different interactions are considered to allow us to model the impact of interventions or to explore alternative ABM outputs.

Day is the unit of iteration for the ABM used for this ABM. Another valid alternative might have been 6-hour blocks (shift lengths) , which are also intuitive for hospital management; see discussion for further details.

3.3 Boarding Design

The design of the Agent-Based Model provides the modeller with an option to implement patient boarding. Boarding represents an active intervention by the hospital and allows the model to reassign patients to an alternative ICU if they cannot be admitted to their ideal ICU due to full capacity. Stochasticity applies to the reassignment of ICU through a multinomial draw from a probability distribution of the likely 'actual ICU' that a patient is admitted to, given their original 'ideal ICU' assignment. We do not include NICU for any patient boarding due to the large differences between neonatal ICUs and adult ICUs. Boarding is not used where to seek to find the 95% Confidence Level that would be needed to service an ICU (without intervention!)

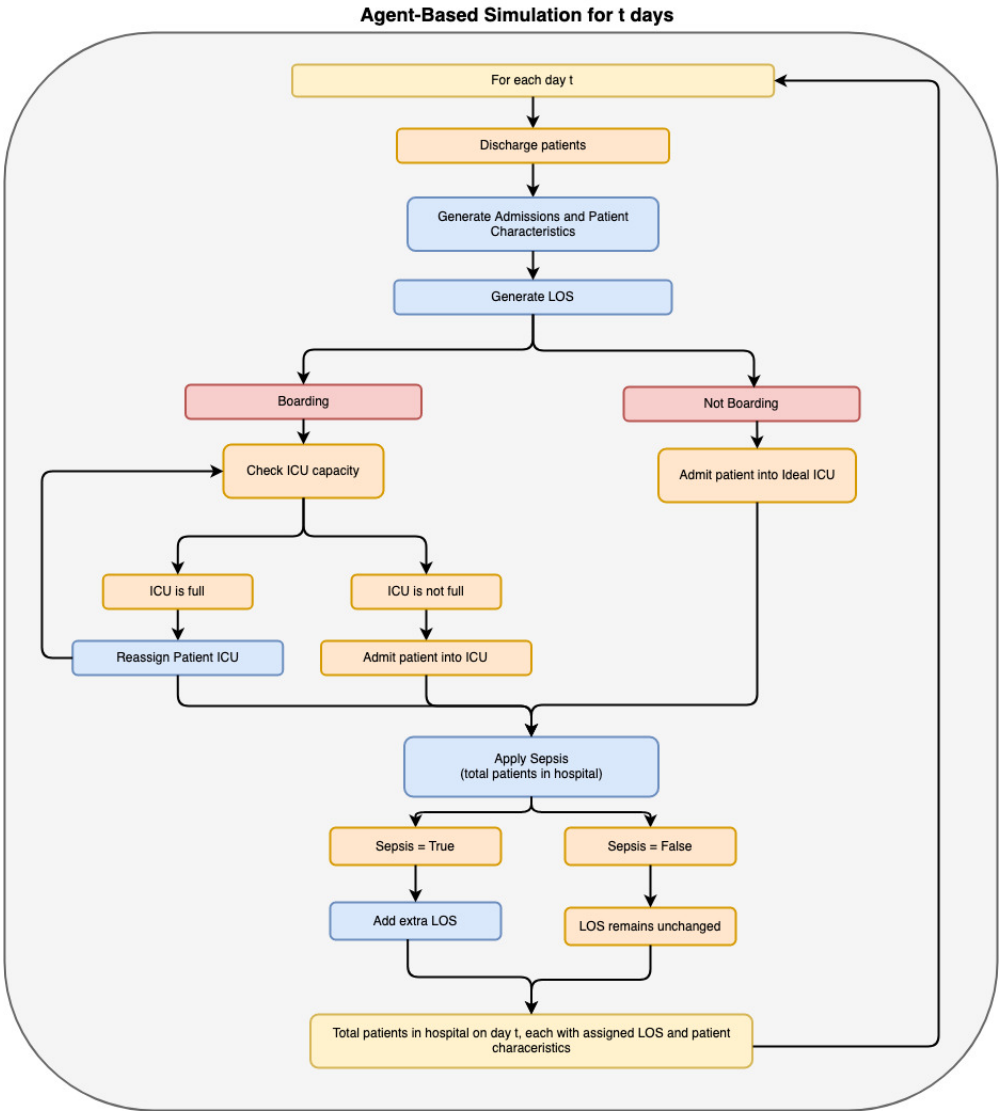


Figure 5: Overview of Agent-Based Model Design

3.4 Sepsis Design

Sepsis is a life-threatening condition that is widely reported in ICU stays and general wards in hospitals [15]. The decision to include sepsis in the Agent-Based Model is based on the prevalence of Sepsis as the most frequent cause of admission to an ICU, the most common cause of death in ICU [16] [17], and a very common cause of hospital readmission in Sepsis survivors [18]. In light of this information, we believe it is crucial to incorporate the effect of sepsis in an ICU patient flow simulation as it leads to disproportionate impact on overall patient LOS, fatality, and hospital costs [19].

Sepsis diagnosis is modelled separately from ICU admissions, and characteristics present at intime, because it develops during a patient's stay in the ICU. For every day that the patient is in hospital, there is a chance that patient develops sepsis. This is represented by every agent being subjected to a draw from a probability for developing Sepsis. The probability of sepsis increases over time; This estimate is explained in further detail in Section 4.4.

In our Agent-Based Model, we choose to exclude sepsis diagnoses with greater severity, such as severe sepsis and septic shock. This decision was made to avoid an overuse of stochasticity

and complexity in one area that could add too much noise to the way patients' LOS is extended, without providing any benefit in capturing relevant hospital dynamics to our problem. However we are aware that mortality and LOS have been shown to increase dramatically with greater disease severity [20];an exploration of this topic could justify further work.

3.5 Simulations

Agent-Based Modelling is a powerful simulation technique that can be naturally be applied to ICU patient flow because typical hospital management systems are composed of frequent 'behavioural' decisions. Here we describe our approach to the simulation process.

We establish five sources of stochasticity in the model, which can be identified as the blue boxes in Figure 5. The full model combines these sources of stochasticity with logical rules to enable the model to capture the system dynamics and generate emergent properties.

We run each model for 1100 days before restarting the simulation. Only days 100- 1100 are counted to allow time for the model to reach steady state. This is repeated to obtain a distribution across multiple runs, which allows us to create 95% confidence intervals for each run and average the Confidence intervals across those runs. For each set of results using the static distributions, we run 1000 simulations over 1000 days. For the Bayes method of updating intime distributions, we run 1000 simulations over 600 days before introducing a heatwave scenario for 60 days.

In accordance with the recommended best practices for Agent-Based Modelling by Hammond [21], we have chosen to work with a simplistic model (no boarding, no Bayes updates, no admission scenarios), to generate results before adding in greater complexity. This allows the modeller to maintain clarity about how each piece of the model affects results, and can greatly facilitate interpretation.

4 Methodology

4.1 Estimating patients who were admitted to wrong ICU

One of the most significant challenges in estimating admission distributions is that we do not have information pertaining to whether a patient is being treated in an ICU that best meets their needs - or whether they are, 'boarding' in another ICU. In other words, patients recorded in one ICU might be better suited to another, and may be artificially inflating the admission numbers to the ICU in which they were treated. Conversely, the other ICU would have artificially deflated admissions numbers. In fact, given that it is impossible to house more patients in an ICU than there are beds, it should be that we never observe an ICU go over-capacity. This must be accounted for to ensure bed estimates are not below the true level required to meet hospital demand.

To address this issue, the services table of the MIMIC-III database was used to identify for which service a patient was admitted. The services table can be used to identify patients physically located at a given ICU but cared for by a team which staffs a different ICU, which can happen for a number of reasons, including bed shortage. A set of rules were then used to assign an 'ideal ICU,' according to services, which can be found in Appendix 4.

In 77.9% cases (47927/61532), this process resulted in the actual ICU being in the list of proposed 'ideal ICUs' , and this ICU was used when estimating admission distributions. In 17.3% cases (10624/61532), one ICU, different to the actual ICU, was identified and this was subsequently used in the place of the actual ICU when estimating admissions distributions. In 4.8% cases (29ddfdf60/61532) it was not possible to distinguish from the service whether the Surgical ICU (SICU) or the Trauma/Surgical ICU (TSICU) should be the ideal ICU. These patients were alternately recorded as SICU and TSICU patients, in line with the split between absolute numbers of ICU stays in each of the 2 ICUs (58.0%/ 41.9%.) Finally, 0.03% (21/61532) cases it was not possible to distinguish from the service whether SICU, TSICU or MICU should be the ideal ICU. Given the nature of the services (dental, genitourinary, Ear Nose Throat and Gynecological,) we placed these patients in the Medical ICU.

The impact of ICU reassignments to 'ideal ICUs' is shown in Figure 6. The main effect of reassignments is to reduce the number of services present within an ICU. The second impact is to change the number of patients who "should have" been admitted to each ICU over the period, thereby correcting the admission distributions to remove the impacts of boarding. The biggest increase in patients was for the MICU, which would have received 5059 additional patients over the period had those patients not been assigned (probably boarding) in other ICUs. The TSICU and the CCU would also have accepted 740 and 258 extra patients respectively. The biggest recipient of boarding patients is the CSRU, which would have hosted 4132 fewer patients had it not accepted patients that would ideally have been housed elsewhere. The SICU also would have received 1925 fewer patients. Only the Neonatal ICU sees unchanged numbers, which can be explained by the inability to adapt infant beds to adult patients and vice versa.

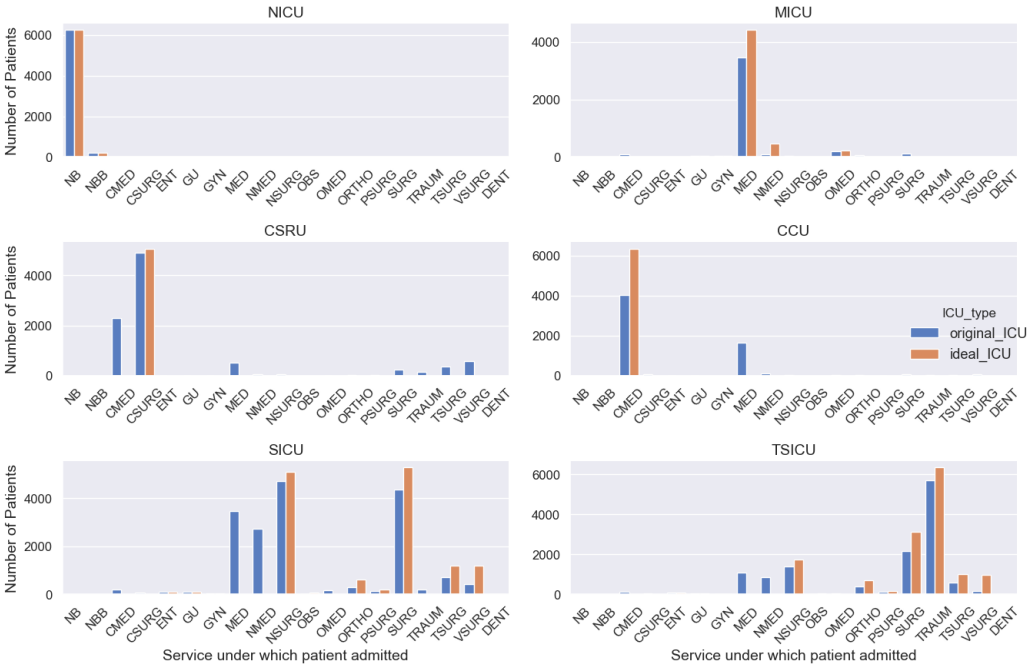


Figure 6: Services per ICU under actual and ideal ICU assignment

A Kolgoromov-Smirnov test showed that patients displayed different hospital LOS and ICU LOS and mortality distributions when they board compared to when they do not board (p = 0.00091, p = 1.49e-09, p = 0.0033.) Figure 6 visualises these results and appears to show that being hosted in a non-ideal ICU is associated with both a longer hospital stay and a shorter ICU stay (the latter perhaps due to non-availability of an ICU bed.)

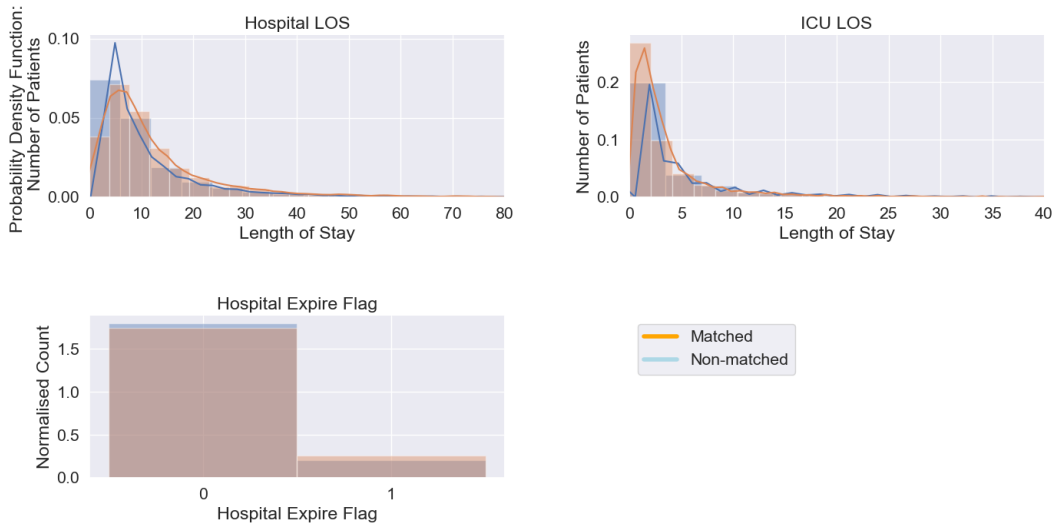


Figure 7: Hospital and ICU Length Of Stay for patients in 'ideal', matching, ICU and 'non-ideal', non-matching ICU

4.2 Estimating admissions distributions

4.2.1 Motivation

In addition to predicting the Length of Stay for an individual agent, another critical component of the ABM is finding a way to model the admissions of patients to the hospital - especially the sub-populations of patients with different characteristics. These two processes combine to create the core of the ABM, whereby each day patients for a given cluster are admitted to each ICU within the hospital and their Length of Stay is drawn from a distribution according to their cluster and characteristics, before discharging patients whose time is up. This is the foundation, onto which additional interactions, changing dynamics and complexities can be layered e.g. sepsis.

4.2.2 Approach

We chose to model the admissions distributions using a multinomial distribution parameterised by an alpha vector where a1...an represent the probability of admitting n = 1...25 patients into the hospital on any given day. There are separate distributions for each cluster and ICU combination, resulting in 24 distributions parameterized by 24 alpha vectors, each summing to one, in total. The multinomial was a natural choice for modelling patient admissions due to its ability to capture some dependence characteristics of the distributions e.g. decreased likelihood of no or high numbers of admissions than would be expected if admissions events were independent.

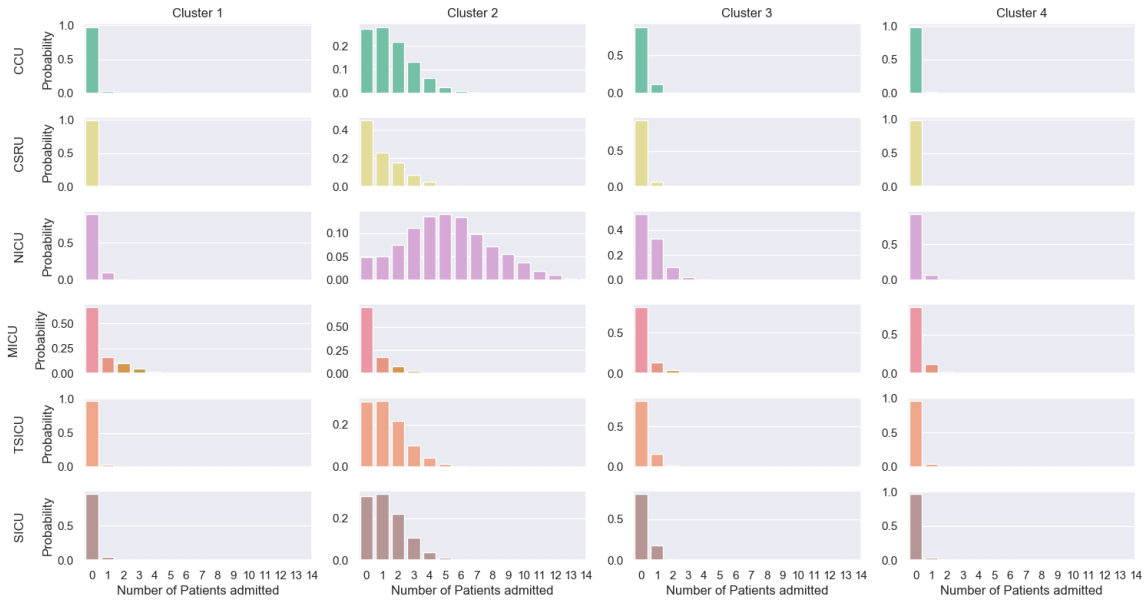


Figure 8: Multinomial distributions for patient admissions by cluster and ICU

4.3 Challenges

4.3.1 Data Anonymity

This challenge of modelling admission distributions is complicated by the anonymisation process for the MIMIC-III data. Dates of ICU stays are randomly shifted by approximately 100 years to protect the anonymity of patients. In this paper we use a collapsed version of the ICU stays table which attempts to reverse this time shift and allows us to estimate admissions distributions in the original timeframe. In doing this, we rely on the assumption that the forward- and back-shifting processes did not affect the admissions distributions in a meaningful way.

4.3.2 The Curse of Dimensionality

A second challenge is the small number of records in the dataset. 61532 rows is split into 4 parts for test, train, validation of Length of Stay Prediction plus clustering exploration. It is further split into 6 according to ICU and a further 4 parts by cluster, leaving buckets of data to estimate admissions distributions as small as 102 which can be seen in Cluster 1 for the CCU in Figure 9. The small size of these individual buckets, especially relative to the large overall dataset, is a manifestation of the curse of dimensionality.

Estimating admissions distributions from a small volume of data is challenging for a number of reasons. First is the possibility of bias. Second is the requirement for 'smoothing' of zero probabilities. In other words, when the data bucket is small, it might be possible to observe a zero probability of admitting 8 patients in cluster 4 to the NICU in a day but a non-zero probability of admitting 9 patients in cluster 4 to the NICU in a day. This probability is falsely estimated as being zero, an artefact of the sampling method. Intuitively, this does not make sense.

To address these issues, we increased the size of our data buckets by reducing the number of features which we assigned to our individual agents (see Achieving the right level of granularity section below.) Where we had originally incorporated patient age, sex and diagnosis into the ABM, we excluded these in favour of 'clustering' patients by Length of Stay, ultimately the characteristic with implications for capacity modelling.

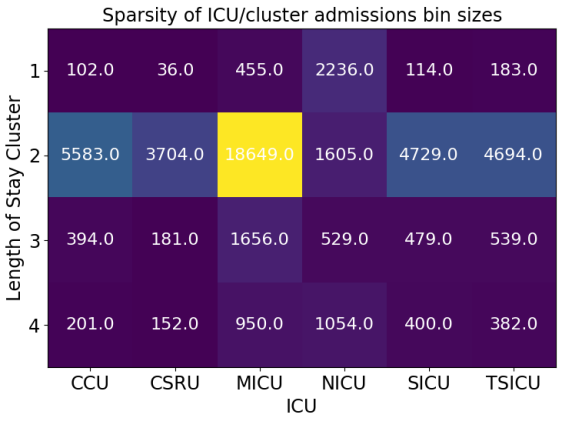


Figure 9: Size of data buckets used to estimate admissions distributions per ICU and cluster

4.3.3 Choosing the Level of Granularity

The decision to reduce the granularity of the agent characteristics we modelled (i.e. using clustering rather than multiple patient features) both decreased the accuracy of our Length of Stay prediction and increased the size of the data buckets we used for admission. This tradeoff- Length of Stay accuracy versus sparsity of data buckets used to estimate admissions distributions- is a key design choice of this ABM and would be relevant no matter which method was chosen to model admissions.

We mitigated the impact of this tradeoff by clustering our patients to create a feature (cluster) which captures Length of Stay variation (see Length of Stay prediction Section 4.5.) In the final ABM, granularity of patient characteristics is only included where it impacts the LOS distribution between groups and allows us to model relevant sub-population dynamics. For example, our approach evolved as we discovered that there is no point in modelling 60-80 and 80-100 year olds with respiratory conditions as separate sub-populations given their behaviour dynamics/outcomes are not different enough to merit reducing the size of the data bucket from which to estimate admission distributions.

4.4 Estimating Sepsis Probabilities

As laid out in Section 3.4: Sepsis design, the exposure of every patient to the chance of getting sepsis every day is an important source of stochasticity in our ABM.

4.4.1 Estimating daily probabilities of developing sepsis

The likelihood of an agent developing Sepsis in the model depends on the amount of time that they have been in the ICU. To estimate these probabilities, we use the data produced by the MIMIC-Extract Pipeline and map the patient's first 24 hours of clinical data in the ICU, including vital signs, laboratory results, device treatments, and interventions, to the ICD-9 code for Sepsis in the Clinical Classification Software. This allows us to create a binary label for whether the patient was diagnosed with Sepsis during their ICU stay. We then apply a machine learning classification method to predict whether a patient will develop Sepsis during their ICU stay. The predictions are scored against the true labels and the best performing machine learning model is selected (full results can be found in Appendix 12.)

Without a prediction model, the clinical data could not be utilised in the ABM because of it is extremely granular state, causing a serious problem of data sparsity. Each combination of time-stamped patient data would occur too infrequently to create any sensible distribution of its occurrence, similar to the challenge for admissions distributions (see Section 4.3.3: Choosing the right level of granularity).

The Sepsis classification model predicts that 9% of patients will develop Sepsis, and we find that those patients have an average LOS equal to 8 days. These results are aligned with reports in the literature regarding to the frequency of septic shock which is estimated at 10.4% (95% CI 5.9 to 16.1%) in studies reporting values for patients diagnosed at ICU admission [22], and ICU length of stay (LOS) for Sepsis patients between 4 and 8 days [23].

To convert these findings to daily sepsis probabilities, we use 1.125% as the baseline probability of an agent developing Sepsis after the second day that they are in the ICU and then extrapolate a linear increase up to day 18. We connect this to the research collected from the Worldwide Data From the Intensive Care over Nations Audit in 2018 [17], which find the rate of sepsis (including severe sepsis) that was identified during the ICU stay in 29.5% patients including 18.0% already at ICU admission. We believe this to be a conservative and reasonable estimate to use in our model.

4.4.2 Incorporating sepsis probabilities into the ABM

If a patient in the Agent-Based Model is assigned a Sepsis diagnosis during their time in the ICU, they will receive an increase to their length of stay. To realistically represent an extended ICU stay due to Sepsis, we calculated the mean difference in LOS between patients with and without Sepsis, based on their assigned ICU, and add it to an agents' remaining length of stay. The table for these additional lengths of stay is in the Appendix 6.

We observe a small amount of variability in average LOS per ICU for Sepsis patients, except for the CSRU and NICU. This is to be expected based on studies that have found the CSRU to exhibit the highest LOS compared to the other specialized intensive care units [24], and the research focused on the vulnerable population of neonates who have a significantly greater risk of infection [25] [26], we believe these to be an acceptable representation of reality for our model.

4.5 ICU Length of Stay Prediction

The key characteristic of each patient - that combines with admissions and sepsis dynamics to generate daily patient numbers - is the Length of Stay. Once ICU patients are 'admitted' to hospital, they are assigned a length of stay, after which time they will be discharged. We use a machine learning approach and explore patient-clustering methods to effectively capture sub-population dynamics in patient outflow.

The motivation for using clusters to predict hospital length of stay follows from the paper by Azari et al [27], who consistently found that using clustering as a precursor to form the training set; binning the LOS into three groups of short, medium, and long stays, gives better prediction results as compared to non-clustering based training sets. Our decision was further supported by the results from the largest studies for predicting ICU LOS in the United States[28] [29] [30], which examined the poor levels of accuracy across individual patients in ICU LoS models (R^2 = 0.18–0.22), and improved precision across ICUs or patient groups (R^2 = 0.60–0.68) [31].

Consequently, we grouped patients into four subpopulations of ICU patients with similar lengths of stay based on a clustering analysis performed on the 20% split of our dataset. These clusters coincide with recommendations from the current literature in ICU LOS prediction. Dimitris et al use machine learning techniques to identify same day discharges, next day discharges, more-than-7 days and more-than-14-day stays [32]. An additional benefit to assigning patients into clusters is that we preserve larger data buckets from which to estimate admission distributions (see Section 4.3.2: The curse of Dimensionality).

Each patient in the Agent-Based simulation is assigned a cluster based on admissions dynamics; then a LOS is drawn from an LOS distribution specific to that cluster. Cluster LOS distributions are generated using interpretable predictive models instead of powerful deep learning models because interpretable predictive models have been shown to result in faster adoptability among clinicians [33]. Decision trees in particular have been successfully applied to many areas of medical decision making due to their ease of interpretation [34].

We ran the following six models for each cluster to find the best 'SGDRegressor', 'GradientBoostingRegressor', 'LinearRegression', 'KNeighborsRegressor', 'RandomForestRegressor', 'XGBRegressor' regression model before hyperparameter tuning. Full prediction results can be found in the Appendix 8.

Our method generates LOS distributions that are less sparse and better aligned with the expected LOS for each cluster. In the figure below, we demonstrate the difference in LOS distributions generated for cluster 1 using a regression model with 30 features, compared to the distribution generated by the same 30 features from the dataset. Figure 10 represents a LOS distribution that has a high probability of being zero days, which decreases steadily until LOS is 5 days. On the other hand, the LOS distribution in Figure 11 can assign a patient in cluster 1 with a maximum LOS of 17 days, but the probability that it will be between 7 and 12 days is zero. The zero probabilities within the range of possible lengths of stay are impractical for the Agent-Based model because the stochastic element will add arbitrary noise to the simulation rather than represent a reasonable LOS for agents assigned to each cluster.

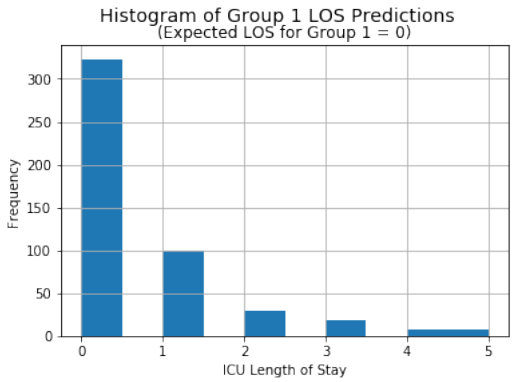


Figure 10: Histogram of Cluster 1 LOS using Predictions

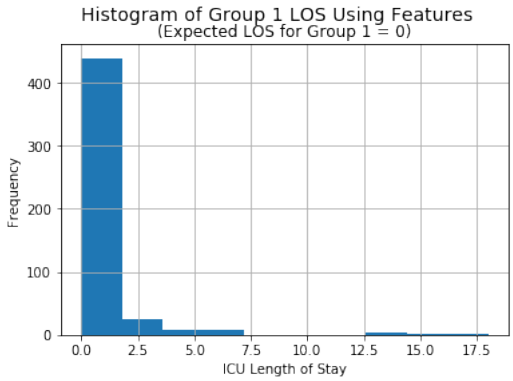


Figure 11: Histogram of Cluster 1 LOS using Features

4.5.1 Subgroup Selection

Cluster one comprises of patients whose expected LOS is zero days. It is important to note that because discharges occur at the start and the end of the day, these patients would not contribute towards capacity numbers on the day that they are admitted. We have chosen to classify patients into group one because we found that the proportion of cases with LOS=0 consisted of 11% of our clustering data but only represented 0.8% of the possible ICU LOS in our data (1/118 unique number of days stay in ICU). Given that the data is right skewed, this group prevents overestimation of LOS that could lead to an inaccurate representation of the capacity required to prevent boarding in the Agent-Based Model simulation.

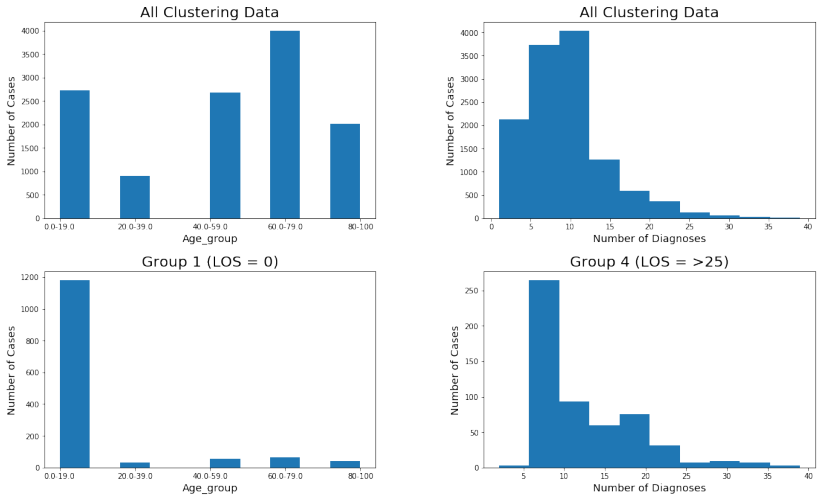
Cluster two was created to include patients whose expected length of stay was between 1-7 days. It is expected that the majority of patients will fall into this group because the median length of an ICU stay in in the MIMC-III database is 2.1 days (Q1–Q3: 1.2–4.6)[35] and LOS distributions are right skewed. As expected, we found that age-group was the only patient feature to distinguish this group from others because it categorises cases without any LOS outliers for a targeted prediction model.

Cluster three includes patients whose expected length of stay is between 8-25 days. We consider these patients to have a 'long' LOS but we differentiate them from the patients in group four who we consider to have a high LOS outlier (above 25 days).

Cluster four has been designed to incorporate patients whose expected length of stay is greater than 25 days. We classify them as high LOS outliers using the method, median + 2SD, because the LOS distribution is right skewed and approximately log normal. We are aware that this method is not useful for the detection of low outliers, but our study prioritizes the representation of cases with above average LOS because they will have a stronger effect on the capacity required to prevent boarding. While studies aiming to identify the characteristics of prolonged stay ICU patients typically define 'prolonged' LOS to be greater than 21 days for teaching hospitals [36] [37], we believe that our method effectively addresses the issue that a small percentage of cases with high LOS outliers (4.49%) represent an important proportion of total inpatient days (38.61%).

4.5.2 Subgroup Features

Following on from the decision to form four clusters, we performed a supervised learning method of Category Boosting Encoder (CatBoost) with a Random Forest Classifier Model to identify important features that could distinguish patients with considerable differences in mean LOS. CatBoost searches for combinations of numerical and categorical features that act as strong predictors, and considers them as a new, more powerful feature [38]. We use this method to identify which combinations of features from our dataset generate a higher importance, and could be combined together to distinguish patients in our dataset with considerable differences in mean LOS.



(a) Comparing Frequency of Age Groups

(b) Comparing Number of Diagnoses per Patient

Figure 12: Differences in Feature Distributions in the Clustering Data

The feature importances from this method can be found in Appendix 5. We used this information to investigate features whose distributions were markedly different between groups and could be used to distinguish individual groups. For example, we see that the distribution of patient age groups is very different when we separate patients whose LOS = 0, and the distribution for diagnosis counts per patient is different when we separate patients whose LOS is greater than 25 in Figure 12. For this reason, we decide to make the age group 0-19 a feature to classify patients into group 1, and a feature for group 4 patients is when diagnoses counts are greater than 5.

The final hand-selected features for each cluster to make LOS predictions can be found in the Appendix 7 and the LOS prediction results per cluster can be found in Appendix 8. As expected, we found that the R^2 score for predictions in clusters 1 and 2 (0.11 and 0.09 respectively) were much lower than the scores for clusters 3 and 4 (0.56 and 0.61 respectively).

4.6 Sensitivity to Changes in Admission Distribution

4.6.1 Motivation

Our approach thus far has been to simulate hospital operations using fixed admissions and Length of Stay distributions. However, there is much evidence to suggest that in the real world, admissions and Length of Stay distributions vary over time. Admissions for hypoglycemia amongst the lowest income families in the U.S. rise by 27% in the week preceding payday[39]. Seasonal patterns of flu cause hospital admission spikes in December and January[40]. Further, we can intuitively understand that small and large shifts in population demographics, infectious disease spread, other population health considerations along with changes in hospital management practices imply dynamic admission and length of stay distributions for a given hospital.

We therefore aimed to test how sensitive our bed requirement estimates are to shifts in admission and other disease pattern shifts using two approaches. The first approach, described below in section 4.6.2, relies on changing fixed parameters relating to the admissions distributions in a way that mimics plausibly realistic situations. The second (Bayesian) approach, described in 4.6.3, assumes a prior distribution and captures shifts in this distribution as part of the simulation process.

4.6.2 Updating the Parameters of Static Prior Distributions

This approach can be summarised as simulating three different scenarios by updating the admissions and length of stay distributions that contribute to the stochasticity of the Agent Based Model. We chose scenarios which are plausible and updated the distributions using numbers evidenced in the literature. The first scenario modelled is a sustained period of pollen levels classified as 'high,' which has been shown to cause up to a 17.23% increase in hospital admissions due to asthma[41]. This was added to the Agent-Based Simulation as binomial draw (p= 0.03, equivalent to 17.23% of the 626 patients over 4170 days for our dataset) that determined whether an additional asthma patient with Length of Stay of 4 days[42] was additionally 'admitted' to the hospital every day.

The second scenario is a sustained increase in pollution, which causes increased hospital cardiovascular admissions[43]- the 85th percentile level of CO levels for example, results in 4% higher cardiovascular ICU admissions. This was added to the Agent-Based Simulation as a binomial draw (p = 0.025, equivalent to 4% higher CV admissions for the 2625 non-surgical cardiac patients over 4170 days in our dataset) that determined if a patient with Length of Stay of 6 days[44] was additionally 'admitted' to the hospital every day.

The third scenario is a prolonged period of heat, which causes an increase of 16% of admissions in the over 75s and and increase of 4% admissions in the under 75s[45]. This was added to the Agent-Based simulation as a binomial draw every for each ICU/cluster combination with these probabilities converted into distributions relevant for our dataset i.e. adjusted to represent the number of over 75s and under 75s present.

Using these modifications, the simulations were re-run to identify any change in bed requirements. Despite the limitation that our scenarios are based upon evidence from shorter time frames and not the longer, sustained time frames that are required to allow the simulation to reach steady state and therefore calculate confidence intervals, we feel that these simulations provide a useful guide for the sensitivity of our results to small shifts in admissions and length of stay distributions.

4.6.3 Modelling smoother transitions using Bayes Principles

So far, we have considered small shifts in the distributions of admissions that are reflected in the variance of the sampling multinomial sampling process under normal conditions and also changes which represent a complete and sudden shift in the underlying distribution- estimated at steady state. To complement these approaches, we aimed to model a gradual shift in the admissions distribution to a different state. The scenario chosen is the heat scenario because this scenario generated observable changes in the previous section. We chose Bayes to model this gradual shift, which allowed us to specify the number of additional patients observed in the literature and see this result reflected in updated priors, rather than requiring evidence of changes in unobserved priors to perform the updates. We acknowledge the possibility for alternative approaches. See discussion for full debate.

The framework used is an extension of the multinomial framework described previously, with the addition that we now assume a prior distribution on the multinomial parameters of the admissions distributions- in the form of a Dirichlet distribution. The setup is described in Figure 13.

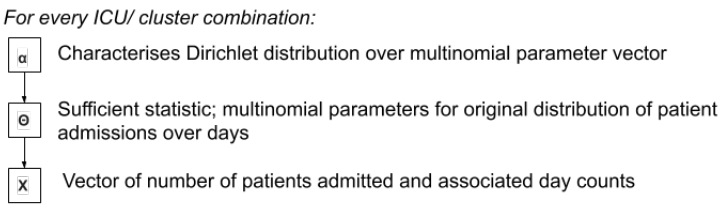


Figure 13: Setup of Bayes Dirichlet-Multinomial framework to model prior distribution on patient admissions

The Dirichlet-Multinomial setup was chosen because the Dirichlet distribution is a conjugate prior to the multinomial; they fall in the same exponential family. The Dirichlet vector alpha in our case represents 'pseudo-counts' - counts estimated from the original distribution of admissions, before we applied changes associated with heat.

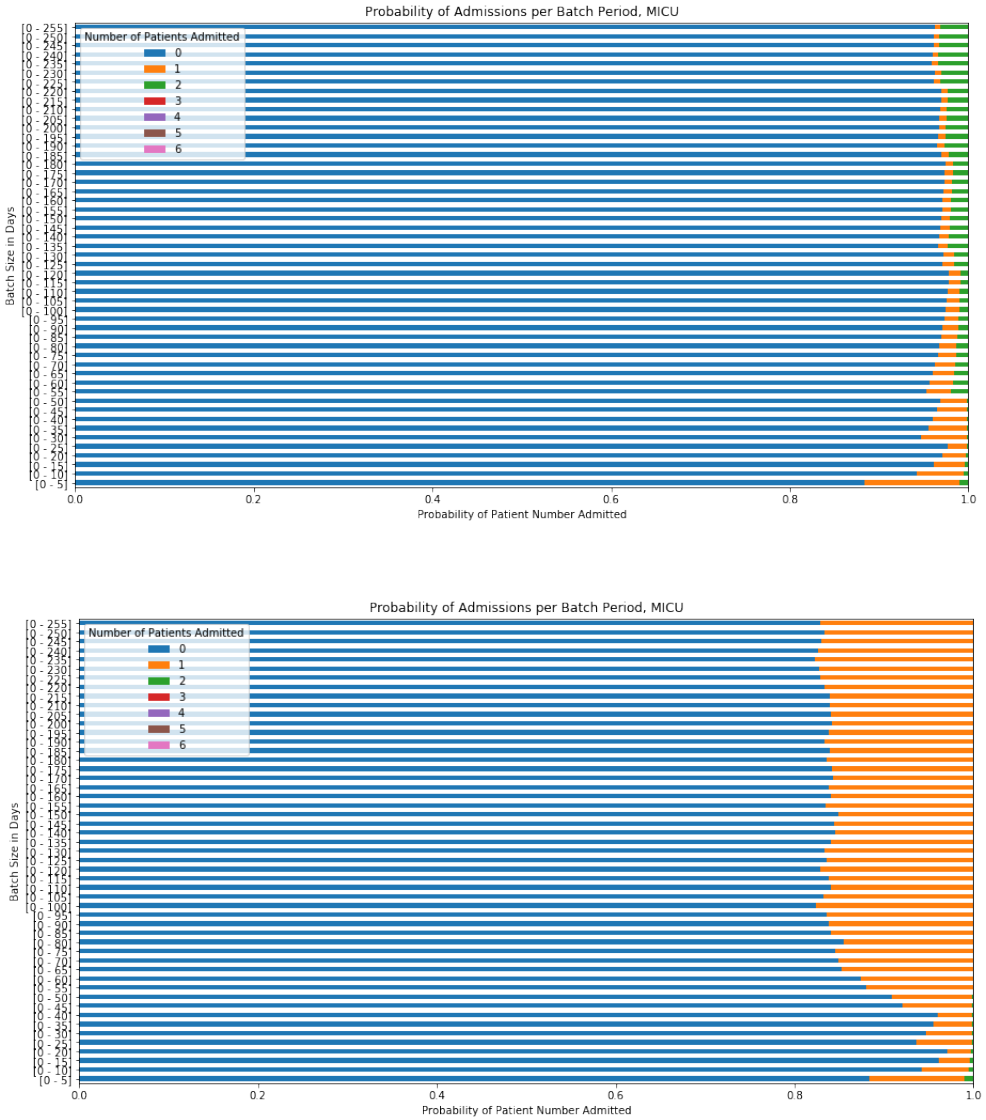
The predictive distribution is the admissions distribution predicted for the next time period. Although a 'true' Bayesian would carry forward information relating to the full distribution, we have chosen to calculate the Expectation of $Dirchlet(N + \alpha)$ to use as the multinomial vector of parameters for the next day's admissions. α is the vector of parameters for the Dirichlet distribution and N is the vector of observations from the latest 'batch' - see Appendix for derivation of update step.

We choose to use a batch size of 5 days to capture a change in admission probabilities quickly, and to use the information from the whole dataset to generate the informative prior, except for the NICU, which is explained in the following section.

4.6.4 Prior Drift

Bayes updates allow our Agent-Based Model to capture a shift in the probability distribution of admissions. However, combining a simulation process with an updating procedure leads to an issue of prior drift- see Figure 14. It can be observed that small biases created by sampling during the simulation process are amplified in subsequent rounds. For example, the probability that on any given day 2 or 3 patients are admitted (the orange and green bars respectively) change over time, despite the fact that in a static simulation there should be no change in the underlying distribution. The manifestation is a drastic shift in admissions in the Agent-Based Model. One way of tackling this issue is to increases the batch size before updating (as this reduces bias in each sample.) However as our goal is to capture a change in the probability distribution of admissions within a few days, this was not an adequate solution.

Figure 14: Comparing the Prior Shift in MICU Probability Distributions of Admissions when using Bayes Updates



To mitigate the impacts of prior drift whilst maintaining the batch size update of five days, we apply weighting methods to combat the presence of prior drift. Firstly, we use add a decay factor of 0.5 to all draws generated by the simulation. This reduces the impact of small deviations in admisssions draws on subsequent draws. Secondly, we apply a weight of 10 to the initial draw from the informative prior. The result of these weighting methods is the elimination of a drifting probability distribution for the number of patients admitted, when simulating the Agent-Based Model, which can be seen in Figure 15.

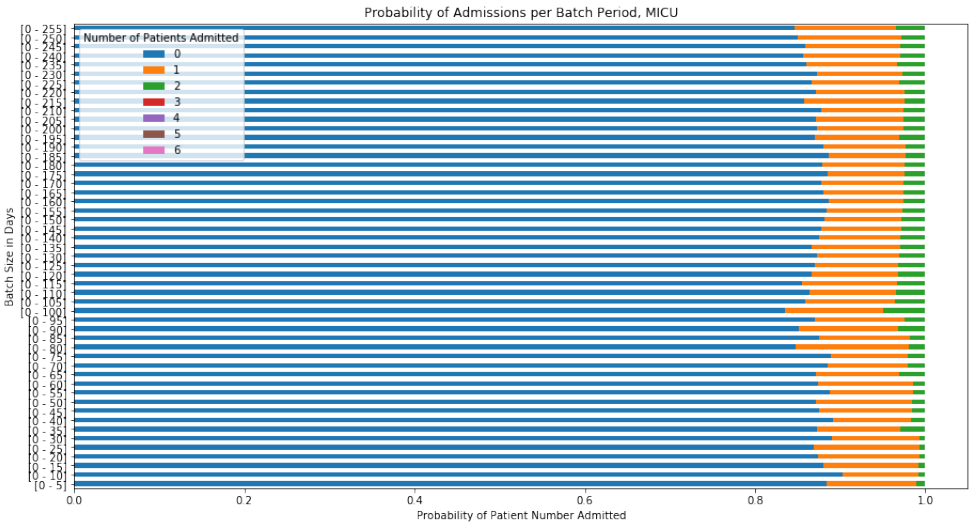


Figure 15: Final Prior Distribution for MICU

A consistent probability distribution is crucial for generating a reliable baseline against which we can test the effects of increased ICU admissions during periods of high pollen, pollution, and during a heatwave.

4.6.5 Bayes Heatwave Simulation

We have chosen to heat scenario that is 60 days- roughly representing a 2-month summer period. See Section 4.6.2 for scenario setup justification.

As we only saw changes to the number of beds required during a heatwave scenario after static changes to the admissions distribution, we choose to simulate only the heatwave scenario in our Agent-Based model using Bayes to capture any changes in admissions patterns for adult ICUs over time. The goal is to capture the 95% confidence interval for bed numbers during a period of gradually (and it is hoped more naturally) updating distributions. We compare the results from the static method and the Bayes updating method in the section 5.5.

The process is that we introduce heat-related changes to the admissions distributions at day 600, which are captured and amplified through the Bayesian updating process described in Section 4.6.3: Modelling Smoother Transitions using Bayes Principles. We continue to add heat-related admissions the distributions for 60 days and the simulation finishes at 760 (including 100 discounted days for the warm-start). This is repeated 1000 times to allow us to calculate average bed levels for the 95% confidence level.

5 Results

5.1 Bed Requirements to Prevent Boarding

Our results indicate that 16, 12, 31, 45, 16, 16 beds would be required in the CCU, CSRU, NICU, MICU, TSICU and SICU in order to prevent over-capacity at the 95% confidence level i.e. patient numbers would remain under capacity 95% of the time. This totals 105 adult beds and 31 infant beds for the entire hospital and is much higher than the 77 adult beds and (estimated) 20 infant beds in the BIDMC currently.

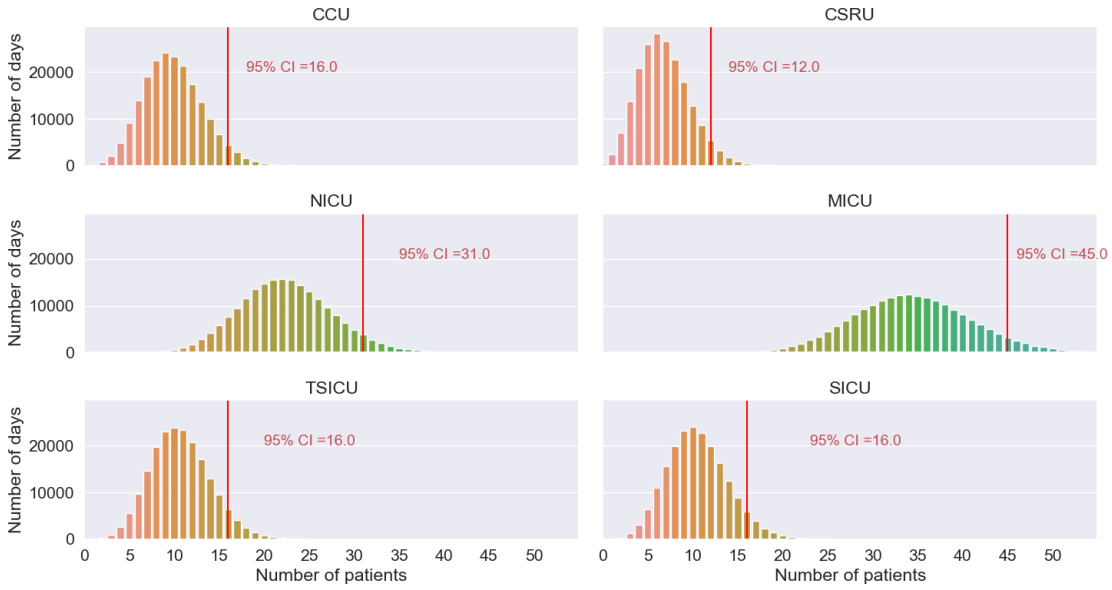


Figure 16: Distribution of days according to patient numbers per ICU; n = 1m days

Bed numbers to meet every Confidence Interval are displayed below. We estimate that at the current bed numbers, BIDMC patient numbers are under capacity 15% , 47.5%, 35%, less than 2.5%, 50% , 95% of the time in the CCU, CSRU, MICU, NICU, TSICU, SICU respectively.

	CCU	CSRU	NICU	MICU	TSICU	SICU
None	15.6	11.8	30.8	45.2	16.3	16.3
Pollen	15.5	11.8	30.8	45.4	16.3	16.4
Pollution	15.8	11.8	30.8	45.3	16.3	16.3
Heat	16.4	12.3	33.5	46.3	17.1	17.1

Table 1: Bed numbers required to service the 95% Confidence Level under different scenarios

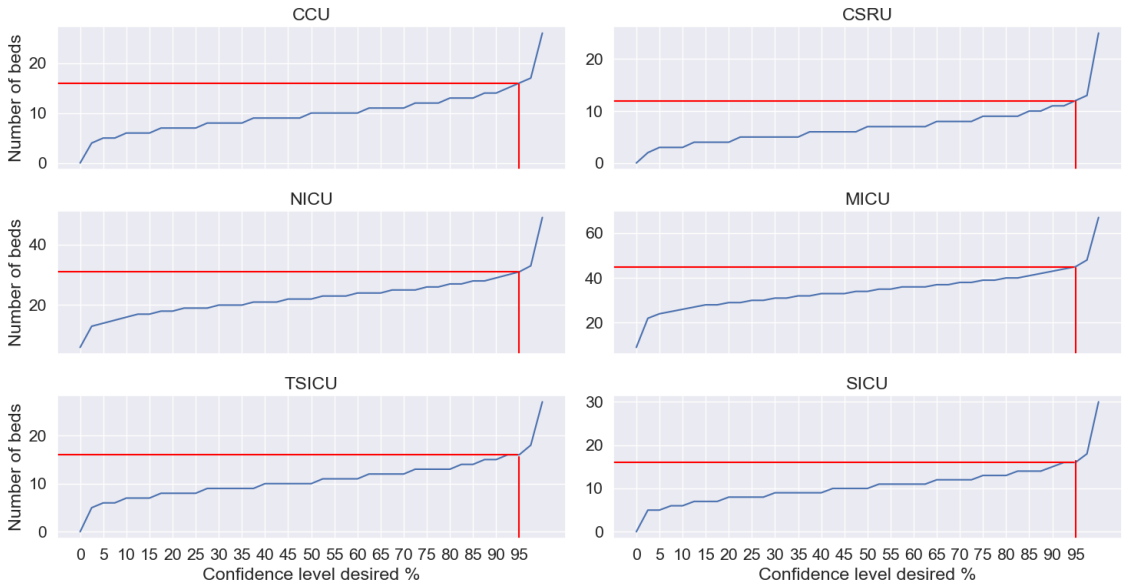


Figure 17: ICU bed numbers required to service all confidence levels; n = 1m days

5.2 Sensitivity of results to changes in admissions patterns - Impact of prolonged periods of high pollen, high pollution and heat

5.3 Changes to the Static Admissions Distributions

Prolonged periods of high pollen and high pollution do not cause a difference to the number of beds required to meet demand at the 95% confidence level . There are smaller increases, but given that bed requirements are rounded up, we do not observe this difference.

In contrast, a period of prolonged heat exposure increases the number of beds required from 16 to 17 in the CCU, 12 to 13 beds in the CSRU, 31 to 34 beds in the NICU, 46 to 47 beds in the MICU, 16 to 17 beds in the TSICU and 17 to 18 beds in the SICU at the 95% Confidence Level. The full distribution shifts are visible in 18

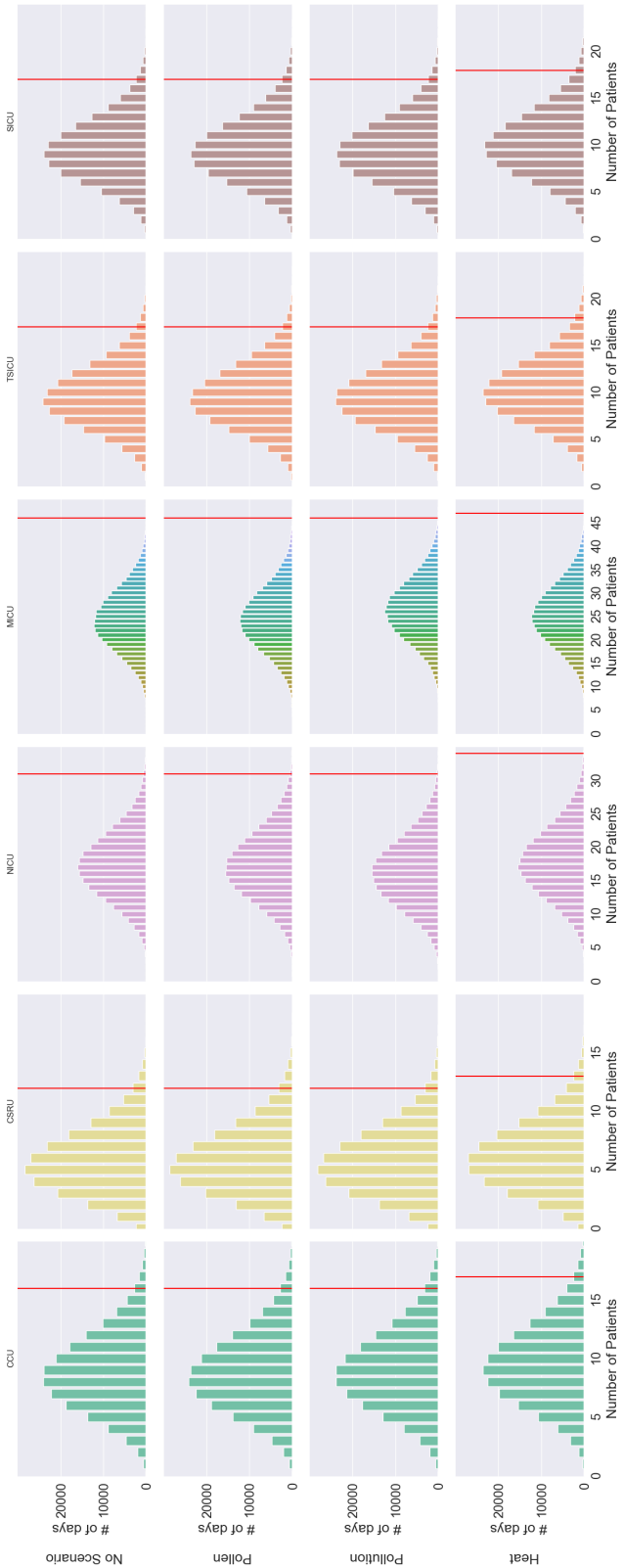


Figure 18: Changes to patient numbers distributions under different scenarios

5.4 Bed requirements to Prevent Hospital Over-capacity

Assuming that beds in all ICUs except the NICU can be adapted for adult needs to some degree (i.e. permitting boarding), we report that 60 adult beds are required at the BIDMC to require being below over-capacity at the 95% confidence level under normal circumstances. This increases to 61 beds in the case of prolonged periods of high pollen (17% increase in asthmas admissions), 62 beds under the scenario of high pollution (4% increase in cardiovascular admissions) and 66 beds under the scenario of prolonged heat (16% increase in admissions for the over 75s and 4% increase in admissions for the under 75s.) There are currently 77 adult beds at the BIDMC.

Figure 6.4 reports the number of beds required at each confidence level for each scenario. We estimate that without active management of patient levels, BIDMC would have patient numbers under capacity more than 97.5% time.

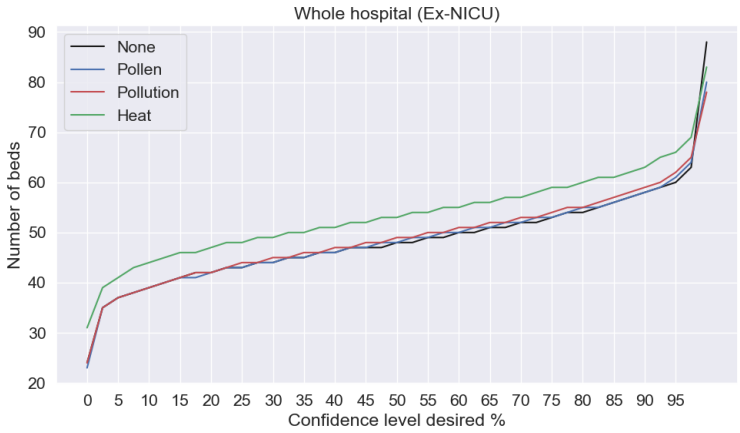


Figure 19: Whole hospital (ex-NICU) bed numbers required to service all confidence levels

5.5 Capturing changes to admissions and patient Distributions using Bayes

We identify how quickly Bayes updates can capture the change in admissions and patients distribution by simulating the heat wave scenario for 5, 10, and 20 days using a batch size of 5 days. We find that it is able to capture the shift for both distributions within 20 days.

When comparing typical admission patterns over a 600 day period to admissions during a 60 day heatwave, we observe that a shift in the distribution of admissions captured by Bayes: the number of admissions per day at the 95% confidence level increases from 23 admissions to 28 admissions between the scenarios (Note here we describe changes in admissions not patient numbers.)

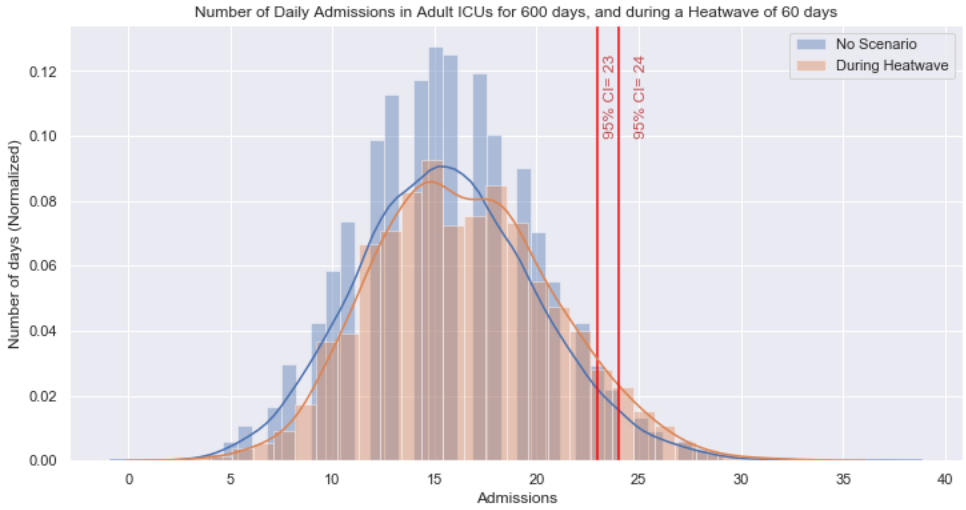


Figure 20: Change in Admission Distribution during Heatwave

The Bayesian approach confirmed that 16, 11, 43, 68, 17, 17 additional beds are required in the respective ICUs in order to meet the increased demand caused by a prolonged heat wave. These figures are inline with the estimates we generated using the static distributions, but are not exactly the same due to the transition period captured in the Bayes approach. The Bayesian approach successfully captured changing admissions representing a realistic heat scenario by updating priors within 20 days.

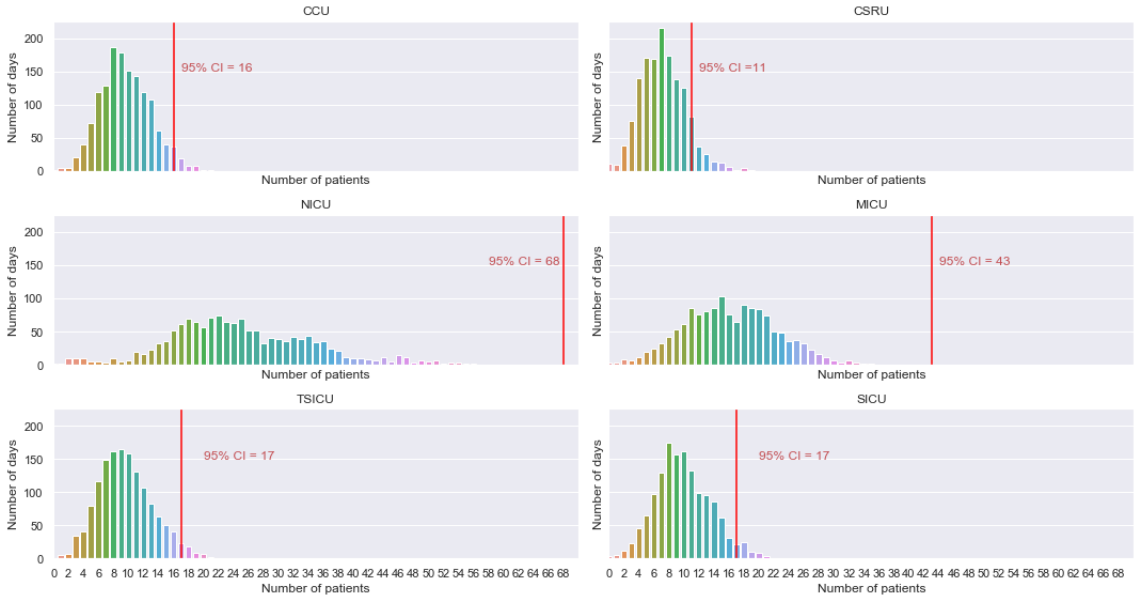


Figure 21: Number of Patients in ICU

6 Discussion

6.1 Bed Estimates under normal circumstances

6.1.1 Evidence for unmet demand

It is readily apparent that, in order to service 95% Confidence Levels for all adult ICUs individually (and therefore prevent boarding on 95% days), a large increase in adult bed capacity would be required (36.3% increase, 105 versus 77 beds). Given that there is a large variation in the amount of time adult ICUs are estimated to spend over-capacity (0 - 95%), we deduce that strategies to actively manage patient flow, including boarding of patients in non-ideal ICUs, play an important role in ICU management at BIDMC.

An insight into what strategies are being deployed is that both ICUs which are net recipients of 'boarders' are also those ICUs with the highest proportion of electives (CSRU - 42.5% and SICU-17.0%) compared to the MICU, which is the biggest contributor of boarders, and admits only 4.2% electives. These results point to boarding in ICUs which can reduce their intake of patients e.g. CSRU delaying operations, being used as a strategy to manage high intake of patients into ICUs which cannot reduce their inflows.

As an extension to our Agent-Based Simulation, we would explore how the dynamics of admissions and Length Of Stay distributions change as ICU capacity increases- with the expectation that as the ICU nears capacity, it takes action to reduce admissions (for example surgical electives) and reduce Length of Stay (for example, discharging patients earlier or moving them to other hospital departments.) In essence, our Agent-Based Simulation demonstrates unmet demand for specialised ICU services that is currently being actively managed through hospital interventions.

At the whole hospital level, we estimate that BIDMC has enough adult hospital beds to cover the demand more than 97.5% of the time. This is important as the impact of delayed admission (to any ICU) is generally acknowledged to be detrimental to patient outcomes[4][5][6].

6.1.2 Boarding in the broader context of healthcare

Reflecting on these findings, we note the mixed evidence as to the harmful effects of boarding on patient outcomes in the literature (see introduction.) Our own summary statistics show a significant difference in ICU, hospital LOS and mortality (see section Estimating patients admitted to the wrong ICU.) To attribute these differences to boarding, further work should explore the impact of potential confounders e.g. do patients who board have other characteristics that make them less likely to die? This would then allow a quantification of boarding on patient outcomes at BIDMC and would inform the debate as to how undesirable a policy to prevent boarding truly is.

There is uncertainty that the extra resources required to maintain additional beds are cost effective when compared to all possible interventions across the whole hospital - including disease prevention and social care/independent living schemes. As servicing a higher Confidence Level for each ICU would necessarily mean accepting higher levels of under-utilisation (or extending demand to patients who do not currently receive ICU service), the cost effectiveness of ICU spend at these higher Confidence Levels is likely to be reduced.

Due to these reasons, we stop short of recommending that bed levels should be increased to meet unmet demand as a result of these findings. Our first contribution in this paper is to provide transparency, a clear articulation of bed numbers required to eliminate boarding for each ICU and to capture all estimated demand for the whole hospital. We recommend that these findings are implemented as part of an analysis considering patient outcomes, experience and costs across the whole health system, not just the ICU.

Secondly, we contribute a methodology which could be adapted to other hospital contexts to provide similar bed level estimates by changing the admissions, Length of Stay, Sepsis distribution inputs and the general hospital setup including the number of ICUs.

6.1.3 Further development of this work

To further increase the value of these simulations to hospital management, we would recommend a program of engagement to tailor the models to better answer questions pertinent to their needs. Such adjustments might include modelling specific interventions, further investigating dependency and clustering dynamics in admissions or incorporating other patient characteristics that affect Length of Stay (in addition to sepsis.)

A key limitation of our methodology is the lack of consideration of sub-day dynamics in Length of Stay distributions. We took the decision to consider day-blocks of time in order to conserve the size of the data buckets from which we estimate admissions distributions. In terms of admissions for those age 20+, this decision seems justified as only a small proportion of individuals have LOS ¡ 1 day (2% for 20-39, 3.1% for 40-59 and 4.7% of 60-79 years olds). However, in the 0-19 age group, 41% of stays are ¡1 day in length. The impact of this is that we are not able to capture the usage of one bed for multiple patients in a given day. This disproportionately impacts our bed estimate requirements for the NICU, which has exclusively 0-19 age group admissions, resulting in higher bed level estimates (45 for the 95% Confidence Interval) than would be needed in reality. It may also mean that our 60- bed estimate for the adult beds in the hospital is likely more conservative, although not massively so given the small number of sub-day stays described above and also the effects of rounding across all stays. To address this limitation, we recommend including sub-day dynamics for younger patients by replacing cluster 1 (¡1 day stay) with 3 clusters for stays of 0-8 hours, 8-16 hours and 16-24 hours respectively.

The other key discussion point we would like to raise is to what level of granularity the Length of Stay distributions and admissions distributions should be linked. The decision to cluster data rather than include patient characteristics was driven by the need to identify features that would enable us to accurately model Length of Stay dynamics whilst simultaneously maintaining data buckets large enough to estimate admissions distributions. Further steps could be taken to improve this methodology or include smaller subpopulations in the simulation. For example, the multinomial has a large number of parameters and that is problematic when data buckets are too small. Alternatives for modelling Length of Stay distributions, which use fewer parameters, and also generate continuous stay lengths, could allow smaller data buckets to be modelled. Simultaneously, this would smooth irregularities generated by the sampling process (such as seeing a non-zero probability for admitting 9 patients in a cluster, but a zero probability for admitting 8 patients.) If combined with a more regular discharge process from the hospital, this would also address the issue of sub-day dynamics mentioned in the paragraph above.

6.2 Bed Estimates under different scenarios

Small shifts in the admissions distributions are already captured within the existing distributions simulated under normal scenarios. By re-running our simulations with different underlying admissions distributions representing 3 scenarios (high pollen counts, high pollution levels, high heat levels), we were able to quantify the magnitude and type of changes that would have an impact on our bed estimates. These updated admissions distributions take into account prolonged shifts in the admissions distribution - that is, the build up of patient numbers under circumstances of consistently higher admissions over a period of time.

Our results show that higher levels of pollen and pollution do not affect the number of beds required to service the 95% Confidence Level, although there small changes which do not amount to a requirement for a full extra bed e.g. 15.8 instead of 15.6 beds required to service the CCU at the 95% Confidence Level; this is due to extra cardiovascular admissions.

Prolonged high levels of heat are associated with higher numbers of beds required to service the 95% Confidence Level, amounting to an extra bed in every adult ICU and 2 additional infant beds in the NICU. These results point to our bed estimates being reliable under circumstances of relatively large shifts in admissions for any individual disease, but not for broader environmental changes that make the entire population more prone to hospital admission, such as heat.

One limitation of this approach is that it also assumes a static underlying admissions distribution-

just a different one. Evidence suggests that for pollen, admissions increase after high pollen levels, but peak with a 4-5 day lag before declining again[41]. This is in contrast to our model which assumes a sudden shift. The delayed effects of pollution on subsequent days after exposure are not taken into account- only increased admissions on the day of high pollution levels. Finally, increased admissions due to pollen/pollution/heat now might lead to reduced admissions in a month's time (for example, the most vulnerable being hospitalised, seeking earlier interventions or even dying earlier.) These dynamics are not reflected when we model change in steady state.

In order to try and capture more gradual shifts in the distributions, we turned to Bayes approaches (see below.) Nonetheless, our estimates simulated under updated static admissions distributions are useful as a bed level guide for the admission distribution extremes.

6.2.1 Bayesian process for simulating a heat wave

Our results demonstrate that a Bayes' method of updating distributions can be used in the Agent-Based Model to incorporate a continued learning technique to capture realistic and unexpected changes in ICU admissions across time. For further work, we could see how it adapts when more than one shift in the admission distribution is applied and this increases and decreases over time.

The key question we propose to discuss here is the value of a Bayesian approach in a simulation context. Although steps were taken to mitigate the negative effects of prior drift, these could not be mitigated entirely. However, we argue that some form of drift or clustering of admissions may resemble the true Data Generating Process.

There is the question as to whether non-Bayesian alternatives could have been used to better model gradually shifting admissions distributions. Our answer to consider the valid alternatives. For example, we could have specified in advance the number of additional patients to add per day to the ABM simulation. This would have pre-empted the answer we were trying to simulate; adding one additional admission per day would have affected the patient distribution in a relatively predictable way. Another alternative might have been to use the stick-breaking process to sample from the Dirichlet without modelling specific scenarios; this would have required heavy computational power to run a large number of simulations based on the admissions distributions drawn.

The advantage of using Bayes versus this method is to generate an element of the natural process of the shifting admissions distributions. A limitation of our approach is the lack of evidence to support Bayes as being a good candidate for modelling this process- but equally there is not much evidence to support the use of other approaches either. This points to extensions to this work in exploring the advantages Bayes versus alternative methods to capture shifting distributions.

7 Conclusion

In this study, we demonstrate how an Agent-based Model can be used in combination with interpretable machine learning techniques to identify bed numbers to prevent ICU overcapacity. Quantifying the specific number of beds required to meet ICU demand at the 95% confidence interval for each specialized ICU, provides hospital resource management teams looking to improve patient care outcomes, with a data-driven tool for decision-making. The option to include boarding within the model also allows healthcare providers to analyze the tradeoffs of specialisation of ICUs and general ICU management.

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Appendices

A Static Variables

Static Features		
admission_type	first_hosp_stay	metabolic/immunity
age_group	first_icu_stay	musculoskeletal
blood	gender	neoplasms
circulatory	genitourinary	nervous
congenital	hospstay_seq	perinatal
diagnoses_count	icustay_seq	pregnancy complications
digestive	ill-defined	respiratory
dod_exists	infectious/parasitic	skin
ethnicity_grouped	injury/poisoning	unclassified
first_careunit	mental	

Table 2: Static Features

B Time-Varying Vitals, Labs, and Interventions

put in a table begintable

C Services to Assigned ICU

	Beds required to service 95% confidence level					
	CCU	CSRU	NICU	MICU	TSICU	SICU
None	15.6	11.8	30.8	45.2	16.3	16.3
Pollen	15.5	11.8	30.8	45.4	16.3	16.4
Pollution	15.8	11.8	30.8	45.3	16.3	16.3
Heat	16.4	12.3	33.5	46.3	17.1	17.1

Table 3: Beds required to service all patients without boarding at the 95% confidence level

Table 4: Service Upon Entering Hospital

Service upon entering hospital	**Description (from MIMIC III database)**	**Assigned ICU**
NB	Newborn - infants born at the hospital	NICU
NBB	Newborn baby - infants born at the hospital	
CMED	Cardiac Medical - for non-surgical cardiac related admissions	CCU
CSURG	Cardiac Surgery - for surgical cardiac admissions	CSRU
MED	Medical - general service for internal medicine	MICU
OMED	Orthopaedic medicine - non-surgical, relating to musculoskeletal system	
NMED	Neurologic Medical - non-surgical, relating to the brain	
PSYCH	Psychiatric - mental disorders relating to mood, behaviour, cognition, or perceptions	
TRAUM	Trauma - injury or damage caused by physical harm from an external source	TSICU
TSURG	Thoracic Surgical - surgery on the thorax, located between the neck and the abdomen	SICU or TSICU
VSURG	Vascular Surgical - surgery relating to the circulatory system	
SURG	Surgical - general surgical service not classified elsewhere	
NSURG	Neurologic Surgical - surgical, relating to the brain	
PSURG	Plastic - restoration/ reconstruction of the human body (including cosmetic or aesthetic)	
ORTHO	Orthopaedic - surgical, relating to the musculoskeletal system	
OBS	Obstetrics - concerned with childbirth and the care of women giving birth	
DENT	Dental - for dental/jaw related admissions	SICU or TSICU or MICU
ENT	Ear, nose, and throat - conditions primarily affecting these areas	
GU	Genitourinary - reproductive organs/urinary system	
GYN	Gynecological - female reproductive systems and breasts	

D Length of Stay Predictions

Feature	Importance
Circulatory	0.248
Admission Type	0.157
Diagnoses Count	0.130
Perinatal	0.117
Infectious/Parasitic	0.037
Genitourinary	0.034
Metabolic/Immunity	0.033
Age Group	0.030
Blood	0.027
Respiratory	0.025

Table 5: cat_boost importances per input feature

ICU	Mean los
CCU	8.387
CSRU	13.977
MICU	5.888
NICU	53.812
SICU	9.515
TSICU	9.850

Table 6: Mean length of stay per ICU for Sepsis patients

Table 7: Length of Stay Prediction Subgroups and Features

CLuster	Expected LOS	Cluster Features	Percentage of Clustering Exploration Data	Mean LOS train/test/validation data
1	0	age group 0-19 admission type = Newborn or emergency perinatal >0 sepsis = False	11.20% of clustering data	0
2	1-7	age group 40-59, 60-79, 80-100	71.48% of clustering data	4
3	8-24	respiratory >0 diagnoses_count >=5 sepsis=True	12.9% of clustering data	14
4	>25	congenital >0 age group 0-19, 40-59, 60-79, 80-100 sepsis = True Infectious parasitic >0 Diagnoses count >=5	4.49% of clustering data	31

Table 8: Length of Stay Prediction Results

Group	R2 scores for all regression models	R2 Score	Best regression model	R2 after hyperparameter tuning
1	SGDRegressor	0.007347531901	GradientBoostingRegressor: 0.08	0.11
	GradientBoost	0.08483720085		
	LinearRegression	0.02647472867		
	KNN Regression	0.009309295672		
	Random Forest	-0.2300258844		
	XGB Regressor	0.07551882294		
2	SGDRegressor	0.09270323329	SGDRegressor: 0.09	0.09
	GradientBoost	0.04071804371		
	LinearRegression	0.06888420161		
	KNN Regression	-0.04758014036		
	Random Forest	-0.03615524859		
	XGB Regressor	0.02759294257		
3	SGDRegressor	-2.03E+21	GradientBoostingRegressor': 0.51	0.56
	GradientBoost	0.5083261174		
	LinearRegression	0.4287217745		
	KNN Regression	0.3775927529		
	Random Forest	0.4888363418		
	XGB Regressor	0.4840271764		
4	SGDRegressor	-1.57E+23	RandomForestRegressor: 0.55	0.61
	GradientBoost	0.5245951847		
	LinearRegression	-2.93E+18		
	KNN Regression	0.3541641769		
	Random Forest	0.5492997342		
	XGB Regressor	0.5416452972		

Table 9: Figure Extract of Admissions Probabilities Table for the MICU

X	Cluster			
	1	2	3	4
0	0.883876	0.049568	0.629908	0.772208
1	0.10582	0.050682	0.291562	0.19521
2	0.010025	0.074909	0.066277	0.02924
...	...	...	...	...
17	0	0.000278	0	0
18	0	0	0	0
19	0	0.000278	0	0

E Bayesian Updates

The multinomial distribution is defined as :

$$\boldsymbol{N} \mid n, \boldsymbol{\theta} \sim \text{MULTI}(\boldsymbol{\theta}, n), \text{ and}$$

$$\text{P}(\boldsymbol{N} \mid n, \boldsymbol{\theta}) = \frac{n!}{\prod_{j=1}^{m} N_j!} \prod_{j=1}^{m} \theta_j^{N_j}$$

The Dirichlet distribution is defined as:

$$\text{DIR}(\boldsymbol{\theta} \mid \boldsymbol{\alpha}) = \frac{1}{C(\boldsymbol{\alpha})} \prod_{j=1}^{m} \theta_j^{\alpha_j - 1}$$

$$C(\boldsymbol{\alpha}) = \int_{\Delta} \prod_{j=1}^{m} \theta_j^{\alpha_j - 1} d\boldsymbol{\theta} = \frac{\prod_{j=1}^{m} \Gamma(\alpha_j)}{\Gamma\left(\sum_{j=1}^{m} \alpha_j\right)}$$

Prior is DIR ($\boldsymbol{\alpha}$). By Bayes Rule, posterior is:

$$\begin{aligned}
\text{P}(\boldsymbol{\theta} \mid \boldsymbol{X}) &\propto \text{P}(\boldsymbol{X} \mid \boldsymbol{\theta}) \text{P}(\boldsymbol{\theta}) \\
&\propto \left(\prod_{j=1}^{m} \theta_j^{N_j} \right) \left(\prod_{j=1}^{m} \theta_j^{\alpha_j - 1} \right) \\
&= \prod_{j=1}^{m} \theta_j^{N_j + \alpha_j - 1}, \text{so} \\
\text{P}(\boldsymbol{\theta} \mid \boldsymbol{X}) &= \text{DIR}(\boldsymbol{N} + \boldsymbol{\alpha})
\end{aligned}$$

Thus if the posterior is DIR ($N + \alpha$), the expected value of θ_j is:

$$\text{E}_{\text{DIR}(N+\alpha)}[\theta_j] = \frac{N_j + \alpha_j}{n + \sum_{j'=1}^{m} \alpha_{j'}}$$

F Sepsis Results

Parameter	Value
C	0.0323
class_weight	None
dual	False
fit_intercept	True
intercept_scaling	1
l1_ratio	None
max_iter	100
multi_class	auto
penalty	l1
solver	liblinear
tol	0.0001
warm_start	False
Result	0.611

Table 10: Best Logistic Regressor models for Sepsis prediction after tuning

Parameter	Value
Bootstrap	True
cpp_alpha	0.0
class_weight	None
criterion	gini
max_depth	8
max_features	auto
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.0
min_impurity_split	NMone
min_samples_leaf	42
min_samples_split	49
min_weight_fraction_leaf	0.0
n_estimators	121
oob_score	False
warm_start	False
Result	0.886

Table 11: Best Random Forest Regressor model paramaters for Sepsis prediction (chosen model)

Metric	Score
roc_auc_score	0.834
accuracy_score	0.886
average precision	0.504
F1 score	0.456

Table 12: Sepsis prediction results