A High-Fidelity Model to Predict Length-of-Stay in the Neonatal Intensive Care Unit (NICU)

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Having an interpretable dynamic length of stay (LOS) model can help hospital administrators and clinicians make better decisions and improve the quality of care. The widespread implementation of electronic medical record (EMR) systems has enabled hospitals to collect massive amounts of health data. However, how to integrate this deluge of data into healthcare operations remains unclear. We propose a framework grounded in established clinical knowledge to model patients’ LOS. In particular, we impose expert knowledge when grouping raw clinical data into medically meaningful variables, which summarize patients’ health trajectories. We use dynamic predictive models to output patients’ remaining lengths of stay, future discharges, and census probability distributions based on their health trajectories up to the current stay. Evaluated with large-scale EMR data, the dynamic model significantly improves predictive power over the performance of any model in previous literature and remains medically interpretable.

Key words:

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1. Introduction

The study of length of stay (LOS) has been a focus in both operational and clinical literature. Clinically, there is a large body of evidence which demonstrates that longer LOS is correlated with hospital-acquired conditions (HAC), adverse drug events, and readmission (Hoogervorst-Schilp et al. 2015, Basques et al. 2015, Ansari et al. 2018, Rinne et al. 2017, Kaboli et al. 2012). For example, Hauck and Zhao (2011) estimated that one additional day in a hospital would increase a patient’s risk of infection by 17.6% and the risk of an adverse drug reaction by 5.5%. In an adjusted analysis of 129 VA hospitals over 14 years (Kaboli et al. 2012), researchers found that an intense focus on efficiency led to decreases in both LOS (down 27%) and 30-day readmissions (down 16%) as well as fewer deaths from any cause at 30 and 90 days after admission.

Financially, the transition from per-diem based payment to a diagnosis-related group (DRG) based payment systems has put pressure on hospitals to use resources efficiently and manage patients’ lengths of stay. Because hospitals are generally paid a fixed payment per admission, the amount of which is determined by the diagnosis-related group. By reducing a day in the hospital, the hospital not only saves on variable costs, such as labor and supplies, but also can accept a new admission and associated payment. In the first year under Medicare’s Inpatient Prospective Payment System (DRG based), the average length of stay fell 9% (Rosenberg and Browne 2001).

In this study, we leverage more than 8 years (2008 - 2015) of electronic medical records (EMR) data from a 71-bed children’s hospital level III/IV neonatal intensive care unit (NICU) in Chicago, Illinois. We focus only on 4624 encounters that were safely discharged home, who represent the majority of NICU patients (89.1%). The mortality rate in our data is less than 5%. The motivation to study patients in the NICU with a focus on length of stay is threefold. First, like other critical care units, the NICU is one of the most data-intensive in a hospital (Anthony Celi et al. 2013, Sanchez-Pinto et al. 2018, Ghassemi et al. 2015a). All the neonates (newborns) under care are being constantly monitored by machines and frequently checked by medical professionals. Secondly, NICU patients’ conditions may be extremely severe, often systematic and life-threatening. This means models built for the NICU are comprehensive enough to be extrapolated to other service lines in a hospital. Another consequence of the NICU patients’ severity is that lengths of stay in the NICU are significantly longer and much more variable than those of adult or
pediatric ICU patients. The median LOS for an adult or pediatric ICU patient is around two days (Verburg et al. 2017, Pollack et al. 2018). The median LOS for patients in this study is 9 days, with a mean of 23.4 days and a standard deviation of 34.7 days. This is partly because adult or pediatric ICU patients are usually discharged to the floor. Recovered Neonatal ICU patients, like inpatient patients, are most frequently discharged home. This has implication for other health care settings with lengthier stays, such as cardiology, neurology and oncology departments (HCUP 2006).

In medical literature, lengths of stay, or time to event data in general, can be modeled using survival analysis techniques. Cox proportional hazard (Coxph) models are most widely used to analyze how patients’ health conditions affect time durations (Collett 2015). Another alternative is the accelerated failure time (AFT) model, which assumes a linear relationship between the health variables and log(LOS). This assumption allows direct regression of LOSs on patients’ health variables with additional assumptions on the distribution of LOSs. Even though LOSs are directly estimated in AFT models, they are usually related to retrospective mortality studies (Verma et al. 1999, Bender et al. 2013, Lee et al. 2016, Richardson et al. 2001, Harsha and Archana 2015). The goal is often to identify the underlying medical relationship between patient severity indicated by a handful of variables and LOS, not to predict prospectively. There is an unserved need when neonatologists attempt to compare their prospective clinical discharge predictions to these models. In addition to being retrospective, these are static models. They generate static estimations per patient using summary statistics of health variables that often change over time.

1.1. Contribution

It is therefore of great interest for neonatologists and hospital administrators to have at their disposal an accurate and interpretable prognostic tool that will inform them about the future prospect of a NICU patient in order to benchmark their estimations, optimize medical care, and carefully plan treatments. In this paper we make the following contributions:

- Our study integrates expert knowledge, comprehensive EMR data, and machine learning algorithm for healthcare operations applications. Unlike recent studies (Rajkomar et al. 2018) that applied machine learning algorithms directly to raw EMR data, every health variable used in our model has been vetted by neonatologists. The codification
of the clinical knowledge in defining and refining the health variables allows the results to be more robust, accurate, and interpretable. This study demonstrates the value in identifying variables with clinical importance over application of machine learning algorithm alone.

• Instead of building a retrospective static model, we construct a dynamic model that takes in comprehensive high-dimensional real-time health data and predicts a patient’s remaining LOS. Using standard machine learning algorithms, random forests of the classification trees family, we achieve highly accurate remaining LOS predictions. Our model has validation $R^2 > 0.8$ after more than 55% of patients are discharged and outperforms the current state-of-art AFT regression models until a substantial part (90%) of the patients’ lengths of stay are reached. For discharge time predictions with rolling time horizons (next week, next 2-week, next month), our model achieves validation AUROCs $> 0.88$ for the first 93% of times until discharge.

• This high accuracy in our model predictions is also a result of our focus on modeling the survival functions directly per LOS per patient. The accurate predictions of the survival functions have other benefits. For example, compared to previous census predictions using point estimations of patients’ LOSs, we can generate the exact probability distributions of the NICU census over time from the dynamic survival functions of each patient. For the hospital administrators, the census probability distributions across time will give them finer granularity in resource allocation and scheduling.

1.2. Literature review

Even though simple linear or log-linear models have difficulty capturing complex medical interactions, in most clinical literature, regression models with a handful of key variables or scores are regularly deployed. Previously reported Cox proportional hazard and accelerated failure time models fall into this category ([Verburg et al. 2017], [Verma et al. 1999], [Richardson et al. 2001], [Bender et al. 2013], [Lee et al. 2016], [Chaou et al. 2017]). In these models, predictions are typically based on the last available measurements or a summary of previous measurements, even though a patient’s health condition is often measured repeatedly over time.

While the majority of the literature focuses on explanatory and retrospective modeling, there have been a few predictive models for ICU lengths of stay. A few studies have responded to the ever-growing data with novel techniques to forecast patient outcomes at
various time points. Ghassemi et al. (2015b) used multivariate time-series data with the multi-task Gaussian process models to predict acuity and mortality in-hospital and after discharge. Rajkomar et al. (2018) modeled a larger, multi-center time-series dataset using recurrent neural networks to predict mortality within 24h, 30-day readmissions and week-long length of stay. Although they achieved high accuracy at several fixed time points, these are static models that process data from a fixed time window to make a fixed-time prediction. Information such as health variables that dynamically changes over time for the same patient was ignored.

Instead of static outcomes at fixed time points, Aczon et al. (2017) applied recurrent neural networks to time-series data and generated a temporally dynamic risk of mortality predictions for Pediatric ICU patients. This setup illustrated another major challenge of predictive modeling within health care applications. The complexity involved in interpreting a “black-box” model, such as a neural network, is likely to discourage medical professionals from sharing their clinical decision-making responsibilities with machine learning algorithms (Sanchez-Pinto et al. 2018, Verghese et al. 2018).

The idea of using multi-state models for time-to-event data in longitudinal studies has a long history (Meira-Machado et al. 2009). These models include time-varying covariates and have the potential to obtain dynamic predictions. However, the complexity of a multi-state model depends on the size of the possible state space and the number of transitions. Due to the high numbers of transitions and the high-dimensional health states in the NICU setting, a naive application of a multi-state model is simply not scalable.

1.3. Challenges

We overcome the high-dimensionality of patients’ health states by modeling length-of-stay transitions instead. Our prediction target is the survival function after each LOS. From the survival functions we can generate the real-time remaining lengths of stay of a patient given their current health variables and the current length of stay.

Not only are the clinical data high dimensional, but their interactions may also be highly indicative of a patient’s health status. We use the following example to demonstrate the benefit of using a tree-based algorithm that could capture these interactions automatically. In the NICU, neonatologists intubate neonates who suffer from respiratory distress. This is a form of invasive therapy, and it interferes with regular oral feeding, which is crucial for growth and recovery. The tree-based method is able to capture this clinical interaction
between breathing and feeding, as well as a patient’s change in respiratory severity. Using three health variables and their interactions, this sampled tree differentiates patients into four groups (from left to right): Feeding problem, No breathing or feeding problem, Breathing recovered, and ongoing breathing problem. Figure 1 demonstrates the survival functions (probability of staying in NICU) for the four groups of patients based on their health trajectory for the past 10-day stays. This tree predicts that neonates without any feeding and breathing problem will be discharged earliest, followed by those with breathing problem but recovered, those with feeding problem and those who continued to have breathing problem were likely to stay the longest.

Figure 1 Tree-based Survival Functions Example. The survival curves show the probabilities of a patient staying in the NICU over time. Intubated: a patient is or was intubated due to breathing problems during the 10th day; LV_max: maximum level of respiratory support for the 10th day, PO_perc: percentage of nutrition by regular oral feeding during the 10th day. Extubated: patient’s respiratory condition improved during the 10th day and the tube was removed. The bottom survival curves are the estimates for patients belonging to the corresponding groups.

The remainder of the paper is structured as follows: Section 2 and 3 introduce the methods and algorithms proposed in this study. Section 4 describes the data that we used to evaluate our method empirically. Furthermore, the analysis of the performance is given in section 5, followed by concluding remarks in section 6.
2. Model

In this section, we overcome the high-dimensionality of patients’ health states by modeling length-of-stay transitions instead. Our prediction target is the survival function given a patient’s current health variables and the current length of stay. We first provide a basic formulation, then transform transition function matrix into survival function matrix, and finally provide implementation details.

2.1. Markov model

A Markov process involves transitions among a finite set of health states $S$. Each potential transition occurs with a rate that depends on covariates including the prior history of an individual’s health state. For each individual $i$, data are collected as health vector $Z = Z_0^i, \ldots, Z_{n_i}^i$ of the transition times from each state $s_k$ to $s_{k+1}$ for $k = 0, \ldots, n_i$ for $n_i$ state transitions with transition probability $p_{s_k, s_{k+1}}(k, k+1) = \Pr(s_{k+1} | s_k, Z_k)$. In an inference task, the object is to estimate the effects of covariates in the estimation of transition probabilities. Given a novel observation starting at an initial state, this model also allows prediction of probabilities tailored to individuals.

2.2. The New Model

As an alternative to the previous model, we propose a model with a set of LOS states $L = 0, 1, \ldots, n$, in which the transition function is $p_{ll'} = \Pr(l' | l, Z_l)$, which is the probability of the future state (LOS $l'$) given the current LOS $l$ and the current observed health vector $Z_l$. Because LOS is monotonically increasing, the transition probabilities from $l$ to $l' < l$ are 0.

The use of state-observation transition functions allows us to model transitions in terms of the observed health vector $Z_l$, dynamically generated from a patient’s available information.
up to Length of Stay $l$, represented by filtration $F_l$. Note that although $l$ is Markovian, $F_l$ is not. And $Z_l$ is not necessarily Markovian.

In what follows, we will split $\Pr(l|\cdot, Z_l)$ into $|L|$ separately trained transition functions $\Pr(l'|Z_l) = \Pr(l'|l, Z_l)$ $\forall l' = 1, \ldots, n$. Each of these functions is given by a survival model, estimated using survival random forest (RSF) (Ishwaran et al. 2008). Next we discuss how to fit the transition functions.

### 2.3. A Survival Model for Transitions

The survival model is a framework for addressing data that contains information on the time to an event. A survival model focuses on the probability $S(t)$ that the event does not occur by time $t$. In our probabilistic framework, for each state (LOS $l$), we have a separate $S_l(t|Z_l)$ defined as the probability that the discharge event does not occur within the next $t$ days, in other words, the Remaining LOS $\text{RLOS} \geq t$:

$$S_l(t|Z_l) = \Pr(\text{RLOS} \geq t | l, Z_l)$$

$$= \sum_{t'=l+t}^{L} \Pr(l'|l, Z_l) = \sum_{t'=l+t}^{L} p_{l'}(Z_l) \quad (2)$$

One of our predictive targets is the Expected Remaining LOS $E_l(Z_l)$, i.e., the expected time to discharge after current LOS $l$ given the observed health vector $Z_l$ at $l$:

$$E[\text{RLOS} | L = l, Z_l] = \sum_{t=0}^{n-l} S_l(t, Z_l) \quad (3)$$

This allow us to translate the transition matrix to a survival matrix

$$
\begin{pmatrix}
S_0(0 | Z_0) & \cdots & S_0(l | Z_0) & S_0(l' | Z_0) & \cdots & S_0(n | Z_0) \\
\vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\
S_l(0 | Z_l) & \cdots & S_l(1 | Z_l) & \cdots & S_l(n-l | Z_l) \\
S_l'(0 | Z_l') & \cdots & S_l'(0 | Z_l') & \cdots & S_l'(n-l' | Z_l') \\
0 & \cdots & 0 & \ddots & \vdots & \vdots \\
0 & \cdots & 0 & 0 & \ddots & \vdots \\
0 & \cdots & 0 & 0 & \cdots & S_n(0 | Z_n)
\end{pmatrix}
$$

(4)

Note that although a transition probability matrix eq. (1) can always be transformed into a survival function matrix eq. (4), the other way around is not necessarily true. Because
each $S_l$ is trained independently, $S_l(0 \mid Z_l)$, $S_l(1 \mid Z_l)$, \cdots, $S_l(n-l \mid Z_l)$ can be used to recover the transition probabilities, which will sum to 1. However, we did not put such constraints across different $S_l$. Therefore, the recovered transition probabilities from $S_0(l \mid Z_0)$, $S_1(l-1 \mid Z_1)$, \cdots, $S_l(0 \mid Z_l)$, 0, \cdots, 0 might not sum to 1. Putting such constraints on these functions will require all of them to be estimated together.

3. Estimation

One motivation of our model is the ultimate incorporation into the electronic medical system. In that scenario, a dynamic model will be trained on all historical data to predict the remaining LOS for individuals that are presently in the NICU. We mirrored this time lag in training and prediction in our current algorithm. To introduce the overall procedure, we first order individuals by their admission dates, then partition the data into the states, LOS $\geq l$. For each $l$, we select the first 80% of patients as the training set. We then apply RSF using training set’s health covariates at $l$, $Z_l^{\text{train}}$ in order to induce the survival function $S_l$ for $l$. The model is then evaluated using the latter 20% individuals’ data $Z_l^{\text{test}}$ and their Remaining LOS (RLOS) at $l$. The following contains an overview of the model algorithm.

**Algorithm 1:** An outline of the algorithm for estimating $S_l$ using RSF

**Data:** All individuals’ LOS $L = 0, 1, \cdots, n$, Remaining LOS (RLOS) at $l$ and corresponding health vectors $Z_l$, dynamically generated from each patient’s all available information up to Length of Stay $l$, $F_l^i$.

1. Order all individuals by their admission time
2. for $LOS \ l$ do
3. Select patients with LOS $\geq l$
4. Select the first 80% patients as the training set
5. Apply RSF using training set’s health covariates at $l$, $Z_l^{\text{train}}$
6. Evaluate $S_l$ using the latter 20% individuals’ data $Z_l^{\text{test}}$ and their RLOS at $l$
7. end

**Output:** A series of $S_l$ for all $l \in L$ that take an unseen health vector and predicts the Expected Remaining LOS

Note that each $S_l$ can be trained separately and in parallel, which significantly improves computation efficiency.
4. Data

Multiple attempts have been made to leverage the rich information stored in electronic medical records (EMR) for accurate predictions (Rajkomar et al. 2018, Aczon et al. 2017). There are, however, few studies that focused on both model performance and interpretability. In the following section, we introduce a data processing scheme that incorporates medical knowledge from the neonatologists and allows us to model the health trajectory dynamically. We tackle the interpretability problem in three ways. First, instead of feeding the raw data directly to a model, we carefully constructed variables that encapsulate the medical relevancy with help from the neonatologists. Secondly, to match the dynamic nature of our model, each variable is characterized by its available time in the EMR system. Thirdly, in order to tackle the high dimensionality problem, we reduced the data dimensionality by aggregating related information and explicitly generated variables to capture known medical or physiological interactions. For a complete break down of variables used in our model see Table 2. Variables summary statistics are available in the Appendices.

4.1. Raw data

We collected the EMRs from the NICU at the University of Chicago Comer Children’s Hospital between Aug 2008 and Oct 2015. The raw data consists of a total of 43,319,934 data points with 4624 encounters and 4612 safely discharged home patients. We define an encounter as a continuous admission into the NICU. A patient can have multiple encounters, though it is rare (0.26%).

The raw data were available in the EMR system at different time points. Some are collected at birth, such as demographics, gestational age at birth, congenital malformations. More dynamic information was collected at various time points during the span of an encounter with the NICU. The dynamic information includes sampled measurements of vitals (e.g. pulse, blood pressure, temperature, weight), machine functional readings (e.g., assisted respiratory rate, mean airway pressure, intravenous fluid rate), exam results (laboratories, neurology, radiology), diagnoses (daily problem list), and interventions (surgeries, procedures, medications).

4.2. Data Processing

Making sure our model is interpretable to the medical professionals, neonatologists participated in every stage of the study. With their guidance, we aggregated related medical
data and generated health variables encapsulating established medical knowledge or physiological meanings. This also reduced the dimensions of our health data significantly, while enhancing the interpretability of the model.

We categorized a variable by two dimensions: medical relevancy and time available in the EMR system. We defined the medical category of a variable based on how it relates to neonatal physiology, using [Gomella et al. (2013)] as a guideline. We then organized data based on their available time within the EMR systems. We classified data as available before birth, available at birth, real-time, daily and available after discharge. For example, due to the time lag between diagnosis and coding, ICD9 diagnostic codes not related to congenital defects are usually available after discharge and before billing.

All information available before birth, such as demographics, financial class, zipcode, and maternal information, as well as information available at birth, such as gestational age at birth, weight at birth, and Apgar scores, are captured in static variables.

### 4.3. Dynamic information

Real-time information consists of machine-generated readings, recorded exam results and interventions. For this type of information, we collected their time-stamps and generated time-averaged dynamic variables for our LOS model. For example, weights are collected regularly through vital machine functions and irregularly through nurse readings. The real-time measurements were aggregated together to generate three variables: daily weight, daily weight change and weekly weight change (rolling) (Table 2). Depending on their medical meaning, some real-time variables may have rolling 3-day averages and rolling weekly averages.

Other information, such as procedures, surgeries, and diagnoses, may not be available in real-time but are updated daily in the system. We consider these as dynamic information as well. For binary variables, we take the daily, weekly, and monthly rolling maximum. For count variables, we take the daily, weekly, and monthly sum (Table 2).

We included procedures, surgeries, and medications in the health status covariates because patients’ health conditions dictate the choices and timings of these therapeutic actions. For example, tracheoesophageal fistula (TEF) repair surgeries are performed to correct the congenital malformations when neonates are healthy enough. Similarly, neonatologists prescribe anticonvulsant medications based on the frequency and severity of seizures.
4.4. Dimension Reduction

To solve the high dimensionality and potential sparsity of our data, we organized and aggregated related information in medically meaningful ways. In what follows, we will use one respiratory variable, which aggregates 220 machine-generated measurements, as an example of such data transformation for dimension reduction. Another example of a metabolic and nutritional variable is in Appendix table 10 and Appendix fig. 8.

![Figure 2](image_url)

Figure 2: The dynamic respiratory variable of one patient tracked over the entire NICU encounter. The patient was admitted right after birth starting with mechanical ventilation and deteriorated quickly, requiring extracorporeal membrane oxygenation. After that, this patient gradually improved over the next month. However, about a week before discharge, the condition deteriorated again but was eventually resolved.

In previous NICU length-of-stay models ([Verma et al., 1999], [Bender et al., 2013]), respiratory variables at various time points are frequently constructed as indicators of health in

<table>
<thead>
<tr>
<th>Respiratory support</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extracorporeal Membrane Oxygenation</td>
<td>7</td>
</tr>
<tr>
<td>High Frequency Oscillatory Ventilation</td>
<td>6</td>
</tr>
<tr>
<td>Mechanical Ventilation</td>
<td>5</td>
</tr>
<tr>
<td>Non Invasive Ventilation</td>
<td>4</td>
</tr>
<tr>
<td>Continuous Positive Airway Pressure</td>
<td>3</td>
</tr>
<tr>
<td>High Flow Nasal Cannula</td>
<td>2</td>
</tr>
<tr>
<td>Low Flow Nasal Cannula</td>
<td>1</td>
</tr>
<tr>
<td>Room Air</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1: Respiratory support types and corresponding severity levels
the morbidity assessment index for newborns (MAIN) (Table 3). However, these variables only captured assisted ventilation and mechanical ventilation at various fixed time points. In addition to being static, these variables ignored several other ventilation methods, such as non-invasive ventilation, high frequency oscillatory ventilation and extracorporeal membrane oxygenation. In comparison, we ordered the respiratory support methods based on the severity and aggregated 220 real-time machine-generated measurements into one respiratory support variable (Table 1). As a result, we were able to track the respiratory support levels of a patient over the entire NICU encounter (Figure 2) using just one variable. As shown in the section example, the respiratory support variable is crucial in predicting patient LOS.

5. Results

Figure 3  Histogram of LOSs for NICU patients. Data is truncated at 95 percentile (94 days).

Patient demographics and other characteristics are summarized in Appendix table 4. The mean and median LOSs are 23.4 days and 9 days. The maximum length-of-stay is 454, and total length-of-stay is 108003 days. The histogram of LOSs for NICU patients are shown in Figure 3.

5.1. Remaining LOS prediction

Our prediction target remaining LOS is defined previously in section 2. We compared the numeric predictions using the statistic $R^2$, the proportion of the variance explained by the
model. The resulted metrics $R^2 > 0.80$ on validation for up to LOS 11, which is after $> 55\%$ of the NICU patients reached the ends of their LOSs and were discharged home. We also implemented the AFT regression model with MAIN scores based on previously published algorithms in Bender et al. (2013) to establish baseline performance on our dataset. The MAIN scores were assessed twice at Day 1 and Day 7, containing information collected beyond the first week in NICU (before birth and after discharge). The baseline AFT model trained using our data gave similar results with validation $R^2 = 0.55$, compared to reported best validation $R^2 = 0.575$.

Figure 4 demonstrates the improved predictive capability of the new model. Validation $R^2 > 0.55$ for 68 days ($>90\%$ of the NICU patients discharged) with the only exception at LOS 57 ($R^2 = 0.52$). This is partly due to our choice of splitting the training set and the validation set by time. Randomly sampled training and validation sets gave validation $R^2 = 0.57$ for LOS 57 model.

5.2. Discharge Time Predictions

To evaluate our dynamic discharge predictions, we used the Area Under Curve for the time-dependent receiver operating characteristic (ROC) curves. In the time-dependent ROC,
cases are those who discharged before next $t$ days, and the controls are those who remained in NICU for the next $t$ days. In the case of next week discharge, cases are those discharged within the next 7 days and controls are those remained until next week.

We focused on the time-dependent AUROCs for three time horizons (next-week discharge, next-2-week discharge, and next-month discharge). Because the short term discharge are often decided by the neonatologists, we did not predict short-term discharges (e.g. next-3-days). All of the metrics were calculated on the holdout encounters at each LOS.

Because the current state-of-art AFT regression model is a static model, we first compared our model using only the Day 1 (LOS 0) data to the AFT model. Even though our model lacked Day 2 to Day 7 information available in the AFT regression model, both models included the same patients for training and validation. As shown in Figure 5, the resulting AUROCs are 0.95 (95% CI 0.94-0.96) and 0.97 (95% CI 0.96-0.98) for next-2-week discharge and next-month discharge. These were significantly higher than those from the AFT regression model, which were 0.89 (95% CI 0.87-0.91) and 0.89 (95% CI 0.87-0.92). Next-week discharge prediction comparison was not shown because the AFT model used information whether a patient stayed until Day 7.

Figure 5  ROC curves for 2 time horizons (next-2-week, next-month) predictions using AFT model with data from day 1 (LOS 0) to day 7 and LOS Model at LOS=0. ROC curves and AUROCs were generated from the same 941 holdout encounters.
As shown in Figure 6, the time-dependent predictions of next-week, next-2-week, and next-month discharge had validation AUROC greater than baseline performance (0.89) for more than 68 LOSs.

5.3. Census distributions over time

The predicted survival function for each patient at each LOS allows us to generate the exact distributions of census over time. Figure 7 shows the probability distributions of census generated for the 70 patients that stayed in NICU on Jan 02, 2015. Because we set up the training data as the first 80% of patients per LOS. This roughly translates to patients that were admitted to our NICU before July 17, 2014. Jan 02, 2015 patients are, therefore, highly unlikely to be in the training set.

6. Conclusion

The increased availability of detailed patient data via the use of electronic health records argues for the integration of medical knowledge, comprehensive data and real-time predictive models. In this paper, we demonstrate the value in identifying medically relevant variables through codification of clinical knowledge, before applying machine learning algorithms. With accurate and interpretable results, neonatologists can compare their clinical
evaluations to our model predictions, review cases with discrepancies, and detect early signals of change in patients’ health conditions that could affect LOS.

We also introduce a dynamic LOS model for NICU patients that inputs real-time health variables aggregated from patients’ clinical data available up to LOS \( l \) and generates dynamic survival functions. The resulted remaining length of stay (RLOS) predictions are highly accurate with validation \( R^2 > 0.8 \) for more than 55% of patients. Our model outperforms the current state-of-art AFT regression model until a substantial part (LOS=68, >90% percentile) of the patients are discharged home.

For the outliers with LOS \( \geq 69 \) days, our remaining length of stay (RLOS) performances decrease past 69 days. However, our future discharge predictions remain accurate for another 29 days. For the outliers, we can still predict with high AUC(> 0.86) after 98 days (95.5% percentile) whether they will stay another 30 days or not.

Our focus on the survival functions also enables us to construct the probability distributions of NICU census over time. We do not currently model new admissions to the NICU. And our model setup and evaluations accommodate new patients that are significantly different from those in the data. With an accurate model for new patient arrivals, we can...
construct future distributions for the entire NICU census, which can lead to better resource planning and care management (Pallin et al. 2013).

One caveat of our study is that we explicitly model discharged-home patients, who represent the vast majority of the NICU discharge dispositions. We can incorporate mortality (<5%) and transfers (~5%) with a competing risk model by adding another dimension to the outcome. However, within our dataset the mortality rate is small, with the number of deaths of the same order as number of health variables in our model. Thus, to obtain accurate predictions of mortality more data would be required.

Our model is trained and evaluated on data from the University of Chicago Comer Children’s Hospital’s NICU. This represents our first attempt to codify neonatology patients’ entire health conditions. Once neonatologists start to benchmark predictions and review cases using our model, they are likely to have feedback and suggestions that could generate better health variables and further improve our model performance. In addition, other hospital systems might have customized data models different from our electronic health system. With modification, our approach can be generalized to similar health systems. Collaboration among multiple health systems will result in more comprehensive data and likely better models, especially for the outliers or to capture mortality.

Thus, our results suggest that when applied to clinically meaningful variables, dynamic methods can dramatically improve prediction performance, especially as patients’ conditions change over their stays in the hospital. These improvements in prediction accuracy, when incorporated into an optimization approach for resource allocation and staff scheduling, can lead to better health outcomes.

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References


Appendix

A. Census distribution calculation

For a cohort of $N$ patients present at time $t = 0$, For $t = 1, 2, \cdots, T$, suppose the probability of $k$ patients remain in the NICU is $\Pr(k \mid N, t)$. This quantity can be calculated recursively. Since probability of patient $i \in 1, 2, 3, \cdots, N$ remaining in the NICU at time horizon $t$ is giving by $S_i(t \mid Z_{l_i})$, we have

**Algorithm 2: The Algorithm for calculating probability distribution of census at time horizon $t$**

<table>
<thead>
<tr>
<th>Input: All $N$ individuals’ $S_i(t \mid Z_{l_i})$ where $l_i$ is the LOS for patient $i$ at $t - 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 for $i \in 1, 2, 3, \cdots, N$ do</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5 end</td>
</tr>
<tr>
<td>Output: $\Pr(k \mid N, t)$ for $k \leq N$</td>
</tr>
</tbody>
</table>

B. Appendix Tables
Table 2: Summary table of the variables in the observed health vector $Z_t$

<table>
<thead>
<tr>
<th>Real-time update</th>
<th>Daily update</th>
<th>Static</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight (grams)</td>
<td>Weight Change (Daily)</td>
<td>Birth Weight</td>
</tr>
<tr>
<td></td>
<td>Weight Change (Since last week)</td>
<td>Preterm</td>
</tr>
<tr>
<td></td>
<td>Gestational Age Corrected</td>
<td>Gestational Age at Birth</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Nonviable</td>
</tr>
<tr>
<td>Developmental</td>
<td>Respiratory Level</td>
<td>Cesarean</td>
</tr>
<tr>
<td>Max Respiratory Level</td>
<td>Respiratory Distress Syndrome</td>
<td>Cesarean</td>
</tr>
<tr>
<td>Min Respiratory Level</td>
<td>Pulmonary Hypertension</td>
<td>Cesarean Cardiac Closure</td>
</tr>
<tr>
<td>Mean Airway Pressure</td>
<td>Meconium Aspiration Syndrome</td>
<td>Congenital Heart: Other Defect</td>
</tr>
<tr>
<td>Fraction of Inspired Oxygen</td>
<td>Anemia</td>
<td>Congenital Circulatory Defect</td>
</tr>
<tr>
<td>Extracorporeal Membrane Oxygenation</td>
<td>Apnea</td>
<td>Congenital Respiratory Defect</td>
</tr>
<tr>
<td>Inhaled Nitric oxide therapy</td>
<td>Bronchopulmonary Dysplasia</td>
<td></td>
</tr>
<tr>
<td>Intubation</td>
<td>Pneumothorax</td>
<td></td>
</tr>
<tr>
<td>Anticoagulants</td>
<td>Intraventricular Hemorrhage</td>
<td></td>
</tr>
<tr>
<td>Surfactant</td>
<td>Tachypnea</td>
<td></td>
</tr>
<tr>
<td>Vasoactive Meds</td>
<td>Pneumothorax</td>
<td></td>
</tr>
<tr>
<td>Alprostadil</td>
<td>Respiratory Level (3-day rolling)</td>
<td></td>
</tr>
<tr>
<td>Surgical Airway</td>
<td>Respiratory Level (biweekly rolling)</td>
<td></td>
</tr>
<tr>
<td>Chest Tube</td>
<td>Respiratory Level (monthly rolling)</td>
<td></td>
</tr>
<tr>
<td>Central Line</td>
<td>Total Chestube Days (weekly rolling)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total Chestube days (monthly rolling)</td>
<td></td>
</tr>
<tr>
<td>Respiratory &amp; Circulatory</td>
<td>Total Volume(mL)</td>
<td>Congenital Diaphragm Hernia</td>
</tr>
<tr>
<td>Nasogastric Tube Volume</td>
<td>Feeding Problem</td>
<td>Congenital Abdominal Defect</td>
</tr>
<tr>
<td>Intravenous Volume</td>
<td>Bowel Obstruction</td>
<td></td>
</tr>
<tr>
<td>Oral Route Volume</td>
<td>Pleural Effusion</td>
<td></td>
</tr>
<tr>
<td>Total Parenteral Nutrition</td>
<td>Pericardial Effusion</td>
<td></td>
</tr>
<tr>
<td>Bowel Resection</td>
<td>Perforation</td>
<td></td>
</tr>
<tr>
<td>Diaphragmatic Hernia Repair</td>
<td>Necrotizing enterocolitis</td>
<td></td>
</tr>
<tr>
<td>Tracheoesophageal Fistula Repair</td>
<td>Diaphragmatic Hernia Repair (Weekly rolling)</td>
<td></td>
</tr>
<tr>
<td>Omphalocele Repair</td>
<td>Tracheoesophageal Fistula Repair (Weekly rolling)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bowel Resection (Weekly rolling)</td>
<td></td>
</tr>
<tr>
<td>Metabolic &amp; Nutritional</td>
<td>Phenobarbital</td>
<td>Down Syndrome</td>
</tr>
<tr>
<td>Antibiotic</td>
<td>Epilepsy</td>
<td>Congenital Spine</td>
</tr>
<tr>
<td>Other Anticonvulsant</td>
<td>Sepsis</td>
<td>Cleft Plate</td>
</tr>
<tr>
<td>Lorazepam</td>
<td>Neonatal Abstinence Syndrome</td>
<td>Congenital Spine Defect</td>
</tr>
<tr>
<td>Dexmedetomidine</td>
<td>Hypotonia</td>
<td>Congenital CNS Defect</td>
</tr>
<tr>
<td>Muscle Relaxant</td>
<td>Bilirubinemia</td>
<td>Congenital Urinary Defect</td>
</tr>
<tr>
<td>Cooling</td>
<td>Retinopathy</td>
<td>Congenital Genital Defect</td>
</tr>
<tr>
<td>Myelomeningocele Repair</td>
<td>Hypoxic-ischemic Encephalopathy</td>
<td>Other Congenital Defects</td>
</tr>
<tr>
<td>Resuscitation</td>
<td>Daily Medications</td>
<td>Total Congenital Diagnoses</td>
</tr>
<tr>
<td>Shunt Insertion</td>
<td>Weekly Medications(rolling)</td>
<td></td>
</tr>
<tr>
<td>Shunt Removal</td>
<td>Neuro Assessment Q1h</td>
<td></td>
</tr>
<tr>
<td>Ventriculostomy</td>
<td>Neuro Assessment Q4h</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Daily Surgeries</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Daily Procedures</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Daily Primary Procedures</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total Surgeries (Weekly rolling)</td>
<td></td>
</tr>
</tbody>
</table>

Continued on following page
Table 2 continued

<table>
<thead>
<tr>
<th>Real-time update</th>
<th>Daily update</th>
<th>Static</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total Procedures (Weekly rolling)</td>
<td>Gender</td>
</tr>
<tr>
<td></td>
<td>Total Primary Procedures (Weekly rolling)</td>
<td>Zipcode</td>
</tr>
<tr>
<td></td>
<td>Total Surgeries (Monthly rolling)</td>
<td>Race</td>
</tr>
<tr>
<td></td>
<td>Total Procedures (Monthly rolling)</td>
<td>Ethnicity</td>
</tr>
<tr>
<td>Socioeconomic Status</td>
<td>Total Primary Procedures (Monthly rolling)</td>
<td>Inborn VS Outborn</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Payer Mix</td>
</tr>
</tbody>
</table>
### Table 3  Respiratory binary indicators in MAIN score

<table>
<thead>
<tr>
<th>Number</th>
<th>Respiratory binary item</th>
<th>Scale value</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>Assisted ventilation beyond 24 h</td>
<td>103</td>
</tr>
<tr>
<td>11</td>
<td>Mechanical ventilation within 24 h</td>
<td>130</td>
</tr>
<tr>
<td>12</td>
<td>Respiratory rate $&lt;30$/min or $&gt;60$/min at 3-24 h</td>
<td>131</td>
</tr>
<tr>
<td>13</td>
<td>Mechanical ventilation at 24 h to 7 days</td>
<td>135</td>
</tr>
<tr>
<td>19</td>
<td>Respiratory rate $&gt;100$/min at 3-24 h</td>
<td>140</td>
</tr>
<tr>
<td>32</td>
<td>Mechanical ventilation beyond 7 d</td>
<td>161</td>
</tr>
</tbody>
</table>

### Table 4  Demographic and other characteristics of encounters

<table>
<thead>
<tr>
<th>Demographics</th>
<th>n=4624</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female Sex</td>
<td>45%</td>
</tr>
<tr>
<td>Cesarean</td>
<td>38%</td>
</tr>
<tr>
<td>Gestational Age (days)</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>254</td>
</tr>
<tr>
<td>Median</td>
<td>232.5</td>
</tr>
<tr>
<td>Pre-Term</td>
<td>53%</td>
</tr>
<tr>
<td>Birth Weight (g)</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>2399</td>
</tr>
<tr>
<td>Median</td>
<td>2554</td>
</tr>
<tr>
<td>Admission Type</td>
<td></td>
</tr>
<tr>
<td>Regular Newborn</td>
<td>76.1%</td>
</tr>
<tr>
<td>Urgent</td>
<td>15.5%</td>
</tr>
<tr>
<td>Elective</td>
<td>2.9%</td>
</tr>
<tr>
<td>Length of Stay (days)</td>
<td></td>
</tr>
<tr>
<td>Median</td>
<td>9</td>
</tr>
<tr>
<td>Mean</td>
<td>23.4</td>
</tr>
<tr>
<td>Max</td>
<td>454</td>
</tr>
<tr>
<td>SD</td>
<td>34.7</td>
</tr>
<tr>
<td>Variable</td>
<td>Mean</td>
</tr>
<tr>
<td>----------------------------------</td>
<td>-------</td>
</tr>
<tr>
<td><strong>Weight</strong></td>
<td></td>
</tr>
<tr>
<td>Daily Weight (g)</td>
<td>2451</td>
</tr>
<tr>
<td>Daily Weight Change (g)</td>
<td>18.7</td>
</tr>
<tr>
<td>Weekly Weight Change (g)</td>
<td>116.8</td>
</tr>
<tr>
<td><strong>Feeding</strong></td>
<td></td>
</tr>
<tr>
<td>Daily Total Volume (mL)</td>
<td>296.1</td>
</tr>
<tr>
<td>Nasogastric Tube</td>
<td>32%</td>
</tr>
<tr>
<td>Intravenous Feeding</td>
<td>28.3%</td>
</tr>
<tr>
<td>Oral Route</td>
<td>36.9%</td>
</tr>
<tr>
<td>Total parenteral nutrition</td>
<td>30%</td>
</tr>
<tr>
<td><strong>Respiratory</strong></td>
<td></td>
</tr>
<tr>
<td>Daily Average Respiratory Level</td>
<td>1.4</td>
</tr>
<tr>
<td>Daily Max Respiratory Level</td>
<td>1.5</td>
</tr>
<tr>
<td>Daily Min Respiratory Level</td>
<td>1.28</td>
</tr>
<tr>
<td>Daily Average Mean Airway Pressure</td>
<td>1.7</td>
</tr>
<tr>
<td>Daily Average Fraction of Inspired Oxygen</td>
<td>9.4%</td>
</tr>
<tr>
<td>3-day Average Respiratory Level</td>
<td>1.5</td>
</tr>
<tr>
<td>2-week Average Respiratory Level</td>
<td>1.7</td>
</tr>
<tr>
<td>1-month Average Respiratory Level</td>
<td>1.9</td>
</tr>
<tr>
<td>Extracorporeal membrane oxygenation</td>
<td>0.2 %</td>
</tr>
<tr>
<td>Inhaled Nitric Oxide Therapy</td>
<td>9.1%</td>
</tr>
<tr>
<td>Intubation</td>
<td>17.6%</td>
</tr>
</tbody>
</table>

Table 5  Weight, Feeding and Respiratory support measurements the encounters, real-time variables
## Congenital Diagnoses of the encounters, static variables

<table>
<thead>
<tr>
<th>Diagnoses</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apgar scores</td>
<td>Mean</td>
</tr>
<tr>
<td>1 Min</td>
<td>7.8</td>
</tr>
<tr>
<td>5 min</td>
<td>8.9</td>
</tr>
<tr>
<td>Diagnosis Counts</td>
<td>8.6</td>
</tr>
<tr>
<td>Congenital Anomalies</td>
<td>34%</td>
</tr>
<tr>
<td>Down Syndrome</td>
<td>0.8%</td>
</tr>
<tr>
<td>CNS:Spine</td>
<td>0.3%</td>
</tr>
<tr>
<td>CNS:Other</td>
<td>2.6%</td>
</tr>
<tr>
<td>Heart:Cardiac closure</td>
<td>17.6%</td>
</tr>
<tr>
<td>Heart:Other</td>
<td>2.7%</td>
</tr>
<tr>
<td>Circulatory</td>
<td>15%</td>
</tr>
<tr>
<td>Diaphragm</td>
<td>0.3%</td>
</tr>
<tr>
<td>Abdominal wall</td>
<td>0.4%</td>
</tr>
<tr>
<td>Cleft Plate</td>
<td>0.8%</td>
</tr>
<tr>
<td>Respiratory System</td>
<td>1.3%</td>
</tr>
<tr>
<td>Genital organs</td>
<td>3.1%</td>
</tr>
<tr>
<td>Urinary System</td>
<td>3.4%</td>
</tr>
<tr>
<td>Other</td>
<td>9.5%</td>
</tr>
</tbody>
</table>

Table 6  Congenital Diagnoses of the encounters, static variables
<table>
<thead>
<tr>
<th>Variable</th>
<th>n=108003</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem List Items</td>
<td>Mean</td>
</tr>
<tr>
<td>Respiratory distress syndrome</td>
<td>39.8%</td>
</tr>
<tr>
<td>Pulmonary hypertension</td>
<td>1.9%</td>
</tr>
<tr>
<td>Meconium aspiration syndrome</td>
<td>1.4%</td>
</tr>
<tr>
<td>Neonatal abstinence syndrome</td>
<td>0.5%</td>
</tr>
<tr>
<td>Sepsis</td>
<td>5.1%</td>
</tr>
<tr>
<td>Bilirubinemia</td>
<td>20.9%</td>
</tr>
<tr>
<td>Retinopathy</td>
<td>2.8%</td>
</tr>
<tr>
<td>Feeding Problem</td>
<td>5.8%</td>
</tr>
<tr>
<td>Anemia</td>
<td>12.3%</td>
</tr>
<tr>
<td>Apnea</td>
<td>14.8%</td>
</tr>
<tr>
<td>Tachypnea</td>
<td>1.2%</td>
</tr>
<tr>
<td>Epilepsy</td>
<td>0.1%</td>
</tr>
<tr>
<td>Hypoxic-ischemic Encephalopathy</td>
<td>0.5%</td>
</tr>
<tr>
<td>Bowel Obstruction</td>
<td>0.3%</td>
</tr>
<tr>
<td>Pleural Effusion</td>
<td>1.1%</td>
</tr>
<tr>
<td>Pericardial Effusion</td>
<td>0.1%</td>
</tr>
<tr>
<td>Periforation</td>
<td>1.7%</td>
</tr>
<tr>
<td>Pneumothorax</td>
<td>1.8%</td>
</tr>
<tr>
<td>Intraventricular Hemorrhage</td>
<td>0.4%</td>
</tr>
<tr>
<td>Necrotizing enterocolitis</td>
<td>3.5%</td>
</tr>
<tr>
<td>Bronchopulmonary dysplasia</td>
<td>4.6%</td>
</tr>
<tr>
<td>Hypotonia</td>
<td>0.2%</td>
</tr>
<tr>
<td>Problem List Counts</td>
<td>Mean</td>
</tr>
<tr>
<td>Daily Counts</td>
<td>4.1</td>
</tr>
<tr>
<td>Weekly Counts</td>
<td>4.0</td>
</tr>
<tr>
<td>Monthly Counts</td>
<td>3.8</td>
</tr>
</tbody>
</table>

Table 7  Problem list items of the encounters, dynamic variables
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surgery in past day</td>
<td></td>
</tr>
<tr>
<td>Resuscitation</td>
<td>0.01%</td>
</tr>
<tr>
<td>Bowel Resection</td>
<td>0.07%</td>
</tr>
<tr>
<td>Diaphragmatic Hernia repair</td>
<td>0.1%</td>
</tr>
<tr>
<td>Shunt Insertion</td>
<td>0.06%</td>
</tr>
<tr>
<td>Tracheoesophageal Fistula Repair</td>
<td>0.01%</td>
</tr>
<tr>
<td>Surgery in past week</td>
<td></td>
</tr>
<tr>
<td>Resuscitation</td>
<td>0.09%</td>
</tr>
<tr>
<td>Bowel Resection</td>
<td>0.5%</td>
</tr>
<tr>
<td>Diaphragmatic Hernia repair</td>
<td>0.65%</td>
</tr>
<tr>
<td>Shunt insertion</td>
<td>0.36%</td>
</tr>
<tr>
<td>Tracheoesophageal Fistula Repair</td>
<td>0.09%</td>
</tr>
<tr>
<td>Neurology assessment</td>
<td></td>
</tr>
<tr>
<td>Every hour</td>
<td>0.27%</td>
</tr>
<tr>
<td>Every 4 hours</td>
<td>82%</td>
</tr>
<tr>
<td>Counts</td>
<td></td>
</tr>
<tr>
<td>Daily Surgeries</td>
<td>0.009</td>
</tr>
<tr>
<td>Daily Procedures</td>
<td>0.20</td>
</tr>
<tr>
<td>Daily Primary Procedures</td>
<td>0.03</td>
</tr>
<tr>
<td>Weekly Surgeries</td>
<td>0.06</td>
</tr>
<tr>
<td>Weekly Procedures</td>
<td>1.1</td>
</tr>
<tr>
<td>Weekly Primary Procedures</td>
<td>0.17</td>
</tr>
<tr>
<td>Monthly Surgeries</td>
<td>0.18</td>
</tr>
<tr>
<td>Monthly Procedures</td>
<td>3.4</td>
</tr>
<tr>
<td>Monthly Primary Procedures</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Table 8   Surgeries and procedures of the encounters, dynamic variables
Wang et al.: Remaining LOS

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medications</td>
<td></td>
</tr>
<tr>
<td>Vasoactive</td>
<td>0.6%</td>
</tr>
<tr>
<td>Phenobarbital</td>
<td>8%</td>
</tr>
<tr>
<td>Antibiotic</td>
<td>34.8%</td>
</tr>
<tr>
<td>Other Anticonvulsant</td>
<td>0.9%</td>
</tr>
<tr>
<td>Lorazepam</td>
<td>2.5%</td>
</tr>
<tr>
<td>Dexmedetomidein</td>
<td>0.06%</td>
</tr>
<tr>
<td>Muscle Relaxant</td>
<td>1.3%</td>
</tr>
<tr>
<td>Alprostadil</td>
<td>0.3%</td>
</tr>
<tr>
<td>Anticoagulant</td>
<td>0.3%</td>
</tr>
<tr>
<td>Counts</td>
<td></td>
</tr>
<tr>
<td>Daily Medications</td>
<td>0.8</td>
</tr>
<tr>
<td>Weekly Medications</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Table 9  Medications given during the encounters, dynamic variables

<table>
<thead>
<tr>
<th>Feeding support</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intravenous</td>
<td>2</td>
</tr>
<tr>
<td>Nasogastric</td>
<td>1</td>
</tr>
<tr>
<td>Regular Oral</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 10  Feeding support types and corresponding severity levels
Figure 8  The dynamic respiratory variable and feeding variable of one patient tracked over the entire NICU encounter.