Real-time forecasting of pediatric intensive care unit length of stay using computerized provider orders

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Objective: **To develop a model to produce real-time, updated forecasts of patients' intensive care unit length of stay using naturally generated provider orders. The model was designed to be integrated within a computerized decision support system to improve patient flow management.**

Design: **Retrospective cohort study.**

Setting: **Twenty-six bed pediatric intensive care unit within an urban, academic children's hospital using a computerized order entry system.**

Patients: **A total of 2,178 consecutive pediatric intensive care unit admissions during a 16-month time period.**

Measurements and Main Results: **We obtained unit length of stay measurements, time-stamped provider orders, age, admission source, and readmission status. A joint discrete-time logistic regression model was developed to produce probabilistic length of stay forecasts from continuously updated provider orders. Accuracy was assessed by comparing forecasted expected discharge time with observed discharge time, rank probability scoring, and calibration curves. Cross-validation procedures were conducted. The distribution of length of stay was heavily right-skewed with a mean of 3.5 days (95% confidence interval 0.3–19.1). Provider orders were predictive of length of stay in real-time accurately forecasting discharge within a 12-hr window: 46% for patients within 1 day of discharge, 34% for patients within 2 days of discharge, and 27% for patients within 3 days of discharge. The forecast model incorporating predictive orders demonstrated significant improvements in accuracy compared with forecasts based solely on empirical and temporal information. Seventeen predictive orders were found, grouped by medication, ventilation, laboratory, diet, activity, foreign body, and extracorporeal membrane oxygenation.**

Conclusions: **Provider orders reflect dynamic changes in patients' conditions, making them useful for real-time length of stay prediction and patient flow management. Patients' length of stay represent a major source of variability in intensive care unit resource utilization and if accurately predicted and communicated, may lead to proactive bed management with more efficient patient flow. (Crit Care Med 2012; 40:3058–3064)**

Key Words: efficiency organizational; forecasting; length of stay; logistic model; medical order entry systems; pediatric intensive care units

Quality of care, access to care, and financial performance are all affected by patient flow within hospitals. Accelerating national trends in inpatient volume and hospital-based healthcare expenditures have created an environment where patient flow and length of stay (LOS) management are critical to patient safety, patient satisfaction, and hospital financial viability (1, 2). As hospital system capacity and economic constraints continue to tighten, high priority has been placed on improving the efficiency and timeliness of care (3–5). Efforts within hospitals, especially large tertiary care facilities, to better manage patient flow are challenged by variability (i.e., uncertainty) in demands for resources, and their complex interdependent systems of care (6–9). These challenges, as recognized by the National Academy of Engineering and Institute of Medicine's joint report, "Building a Better Delivery System: A New Engineering/Healthcare Partnership," lend themselves to systems engineering approaches of study and solution development (6, 10). This study represents the development of a systems engineering tool to be deployed as a real-time decision support application for improved management of patient flow through intensive care units (ICUs) and hospitals.

Patient LOS is a major source of variation that determines flow and demand for ICU and other hospital resources (11–15). Obstructions in ICU flow may cause adverse effects within hospital systems through unavailability of services, delays in care, and patients being treated in suboptimal care areas. ICUs reject admissions with varying rates due to lack of available resources such as beds and staff. Critically ill patients are

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known to have better survival rates when treated in ICUs, with refusal being associated with increased risk of in-hospital mortality (16). In addition, lack of beds commonly creates delays in the operating room, postanesthesia care unit, and less frequently may cause surgical case cancellations (17, 18). Delays in patient flow to the ICU disrupt patient care by postponing surgical start times or by requiring postoperative patients to remain in the postanesthesia care unit for lengthy periods of time. Decisions to delay scheduled surgical procedures may incur heavy costs for operating room idle and staff overtime. Similar access delays are created in the emergency department, where excessive boarding has been associated with significant increases in mortality rate (19, 20). ICUs are not always the root cause of these delays. Most patients exit the ICU to lower level care areas where bed unavailability creates a common barrier to outgoing transfers (9, 21). Patients awaiting transition consume valuable ICU resources that may be more beneficially directed toward patients waiting or refused access (22). Patient flow through the ICU is a major driver of hospital operations affecting patient safety, quality of care, and financial performance.

ICUs are highly integrated into hospital systems stressing the need for effective coordination, communication, and timely information transmission. Daily ICU patient flow management requires ensuring appropriate staffing levels, deciding to accept or refuse patient admissions, timing and executing admissions, and transfers to minimize patient wait time and refusals. These functions require projecting discharge times and future resource needs for patients. In the hospital studied, projections are based on human experience and intuition supplemented by daily morning status reports. Information systems such as electronic whiteboards or bed boards are useful in examining the current state of a unit or hospital but do little to assist in projecting the future, which patient flow management is based on.

There has been significant effort in critical care medicine and operations research directed toward predicting patient LOS. From a clinical perspective, LOS is often modeled as an outcome associated with health status and risk of adverse event or mortality (i.e., primary outcome) (23–27). The Acute Physiology and Chronic Health Evaluation model is a well-known example (23). Regression models or algorithms are developed using physiologic, diagnostic, and demographic information to make predictions on or near arrival. Accuracy of predictions is evaluated through calibration. Mean predicted LOS is compared to mean observed LOS within and across specific ICU patient cohorts. From an operational perspective, LOS is modeled probabilistically. LOS distributions are characterized using Markov models, phase-type, or mixed distributions with the aim of discerning long-stay patients that comprise the long tail often seen in LOS distributions (27). These models may be incorporated in queuing systems or simulations developed to understand and improve resource allocation and long-term strategic planning (28, 29).

The objective of this study was to develop a novel model to produce real-time forecasts of patients' future ICU LOS using provider orders. Probabilistic forecasts spanning 72 hrs into the future are generated from recent orders (i.e., within previous 6-hrs) for each patient. Forecasts based on orders are updated to reflect dynamic changes in patients' conditions. Probabilistic forecasts are evaluated for accuracy and calibration in predicting future time of discharge. The ultimate goal of this research is to incorporate the LOS prediction model into a generalizable forecasting tool used in clinical practice to support proactive bed management and improved ICU patient flow.

METHODS

Design and Patient Data Collection. We conducted a retrospective cohort study of 2,178 consecutive pediatric intensive care unit (PICU) patients over a 16-month time period. The institutional review board approved this study. We excluded 70 (3.2%) patients that died in-hospital and 46 (2.1%) patients with missing or incoherent data. The final cohort consisted of 2,062 patients with an average age of 6.75 yrs ranging from <1 (23%) to 21 yrs. All patients were cared for in a 26-bed PICU, which is part of a 180-bed children's hospital located within an urban, academic medical center. Patients' source of admission was the operating room (39%), pediatric emergency department (26%), intrahospital transfers (18%), and referrals from external healthcare facilities (17%). PICU providers used a computerized provider order entry (POE) system (Eclipsys Sunrise, Chicago, IL) to directly enter all orders including diets, activity, medication, laboratory tests, radiology tests, and procedures.

PICU LOS, source of admission, readmission status, age, and all time-stamped provider orders 6-hrs prior to PICU arrival until PICU discharge were collected. An expert panel of three pediatric physicians and one nurse selected key orders hypothesized to be predictive of LOS. Selected orders fell into the following categories: activity, consults, diet, extracorporeal membrane oxygenation (ECMO), foreign body, laboratory, mechanical ventilation, enteral medications, infused medications (vasoactive, opiate, other), injected medications (electrolytes, sedatives, muscle relaxants, other), and transfusion. Each of the categories was composed of orders. In total, 770 unique raw orders in POE were mapped to 60 meaningful orders recognized by the forecast model. For example, raw orders for "Regular Diet," "Regular Diet—Appropriate for age," and "Regular Diet—Appropriate for age PEDs" were all mapped to "Regular Diet." Similarly, there were 30 unique dietary orders mapped as withhold food, clear liquid diet, full liquid diet, formula/human milk, or regular diet. Additional information such as ventilation frequency (i.e., continuous vs. nightly) or laboratory order frequency was also used to stratify order groups. Preliminary discrete-time logistic regression models were displayed to the expert panel in an iterative process to further refine order selection.

Model Development. Patients' future LOS was predicted using survival analysis. Discrete-time logistic regression models were developed to predict the probability of a patient being discharged within each 6-hr interval up to 72 future hours. The 72-hr forecast window was chosen by PICU bed management personnel to reflect practical requirements to support daily patient flow management functions. Twelve separate models (i.e., 72 divided by 6 hrs) were used to predict likelihood of discharge across each interval. The models estimate the probability of discharge in a specific interval given the patient will be present in the interval prior. The set of model estimates are joined by the following function where: (a) represents an individual model's probability estimate, and (p) represents the joint probability estimate for the (ith) future time interval:

$$p_i = p_{i-1} \times \frac{(1-a_{i-1})}{a_{i-1}} \times a_i$$

This produces a coherent probability distribution forecasting a patient's probability of discharge with emphasis on predictions closest to the current time (i.e., $i = 0$) being most accurate (30). It is assumed that all patients are eventually discharged (i.e., probability distribution must sum to 1). Within this framework, the probability of a patient being discharged after 72 hrs is calculated by subtracting the cumulative sum of probabilities in each interval from 1. Thus, 13 discrete probability estimates are forecasted.

The joint model is conditioned on fixed information such as a patient's age, source of admission, and readmission status, but is updated in near real-time based on dynamic information such as patient's current LOS, temporal factors, and provider orders. Fixed and dynamic information serve as model predictor variables each time a forecast is made. Patients' current LOS is grouped as either being short stay (≤3 days) or long stay at the instant the forecast is made. Temporal information includes the day-of-week and time-of-day (i.e., grouped by midnight to 6 AM, 6 AM to noon, noon to 6 PM, and 6 PM to midnight) the forecast is made. Dynamic order information is extracted from computerized POE in the interval 6 hrs prior to forecast time. For each patient's 6-hr order extract, all 60 orders are indicated as either present or not. For example, if a lactic acid laboratory order was placed for a patient within the past 6 hrs, this variable was listed as present. Medications were grouped by type and administration route. In addition, counts of medications by administration route (i.e., enteral, infusion, injection) were examined as predictor variables.

An example probabilistic forecast, at three time points (i.e., continuously updated) during a patient's LOS may be seen in Figure 1. Output forecasts are updated over time to reflect changes in a patient's conditions based on orders. The baseline (i.e., time zero) for each forecast is the present time. The example forecasts are for an 8-yr-old patient admitted through the emergency department, with the leftmost plot representing the patient 6 hrs into their PICU stay. Within the previous 6 hrs, the patient had present orders for three infused medications, three injected medications, continuous ventilation, either activated partial thromboplastin time or D-dimer laboratories with a frequency of <6 hrs and clear liquid diet (see order set below plot). At this point, the patient is likely to be discharged after 3 days, as evident by the forecast distribution. The middle plot represents the same patient 58 hrs into their stay, with an order set reflecting a progression in health status, but still uncertainty about future LOS exists. The right plot shows again the same patient with an order set indicating further progression and likely discharge within the next 18 hrs. The temporal predictor variables (e.g., time-of-day) produce the harmonic peaks most evident in the middle plot. This is designed to account for PICU processes (e.g., rounds, staff shift changes) that make it most likely for all patients to be discharged during certain times of the day.

Model Evaluation and Order Selection. The model was evaluated for accuracy using: 1) comparisons of forecast expected discharge time with observed discharge time, 2) rank probability scoring, and 3) calibration curves. First, a comparison of predicted and actual discharge times was conducted to better understand the practical utility of the model. The proportion of accurate forecasts for all patients as they approach their observed discharge time (e.g., 72, 64 hrs … 12 hrs, 6 hrs) was captured. A forecast was defined accurate when its expected (i.e., most likely; peak probability) discharge time was within 12 hrs of the observed discharge time. Second, the rank probability score (RPS) was applied. The RPS has been demonstrated to be an effective measure for evaluating the quality of probabilistic forecasts (31). The RPS assesses the variance (i.e., certainty) of probability estimates around the actual observation (i.e., discharge time). A forecast that places a high concentration around the time of actual observation is more accurate and certain than a forecast distribution with higher spread. RPS was used to evaluate the accuracy and certainty of each patient's set of updated forecasts and also formed the basis for selecting the most highly predictive orders. The RPS is a measure of the difference (i.e., integral) between the cumulative distribution of a forecast and actual observation and has been shown to minimize mean absolute error (32). An example of how the RPS is measured for a patient discharged between 18 and 24 hrs from forecast time may be seen in Figure 2. This measure was calculated for each updated real-time forecast (n = 29,749) for all patients in the cohort. A third measure of forecast calibration was assessed graphically by comparing the mean probability of discharge to observed probability for each model interval. The calibration curve was used to ensure that no systematic bias in either under- or overpredicting probability of discharge existed.

The exact usefulness of orders in predicting LOS is further scrutinized by comparing the forecast model incorporating provider orders as predictors (i.e., order-based model) to a similar forecast model solely relying on fixed and temporal variables (i.e., empirical model). The empirical model is created by the same joint logistic regression methodology using fixed (i.e., patients' age, source of admission, readmission status) and temporal (current LOS, day-of-week, time-of-day) predictor variables only. The order-based model incorporates fixed, temporal, and order-based predictor variables. This comparison allows for an isolated evaluation of the predictive value of provider orders.

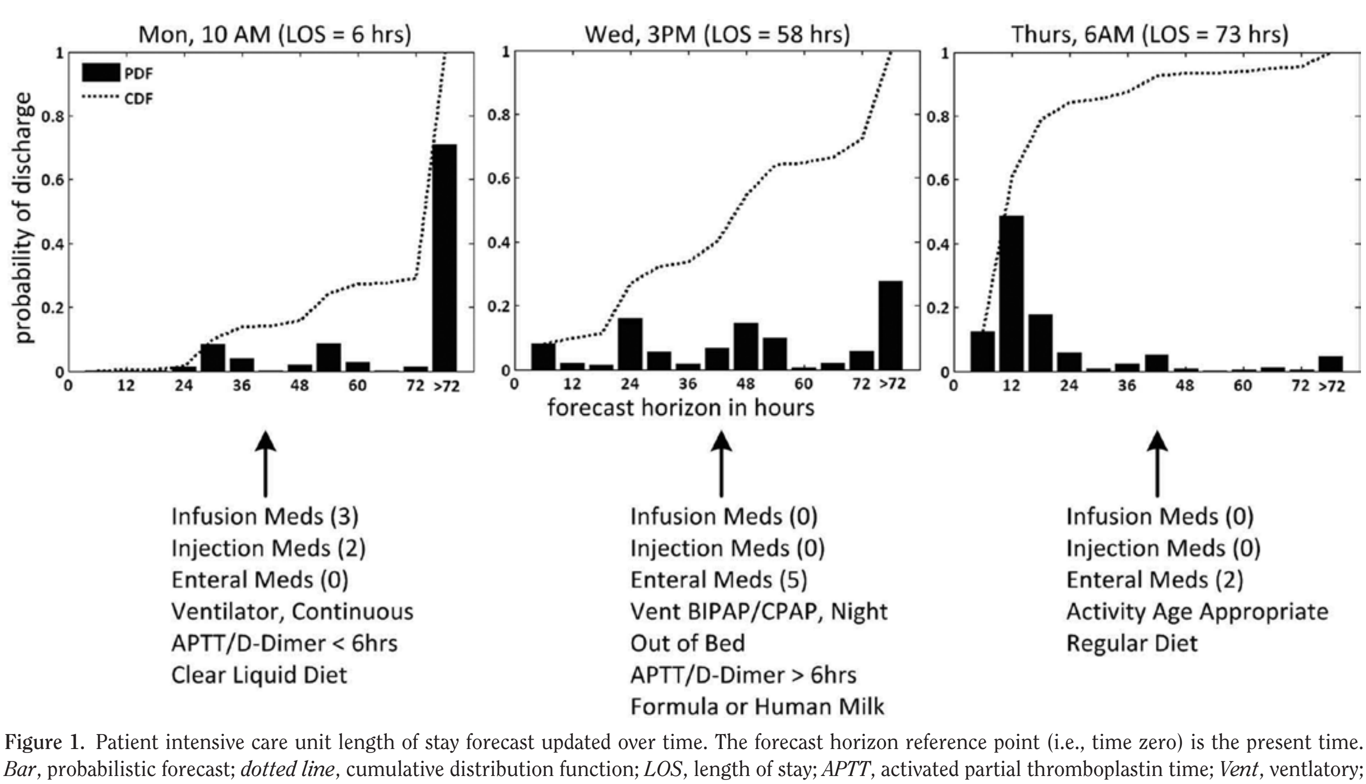

Figure 1. Patient intensive care unit length of stay forecast updated over time. The forecast horizon reference point (i.e., time zero) is the present time. *Bar*, probabilistic forecast; *dotted line*, cumulative distribution function; *LOS*, length of stay; *APTT*, activated partial thromboplastin time; *Vent*, ventlatory; *BIPAP*, bilevel positive airway pressure; *CPAP*, continuous positive airway pressure.

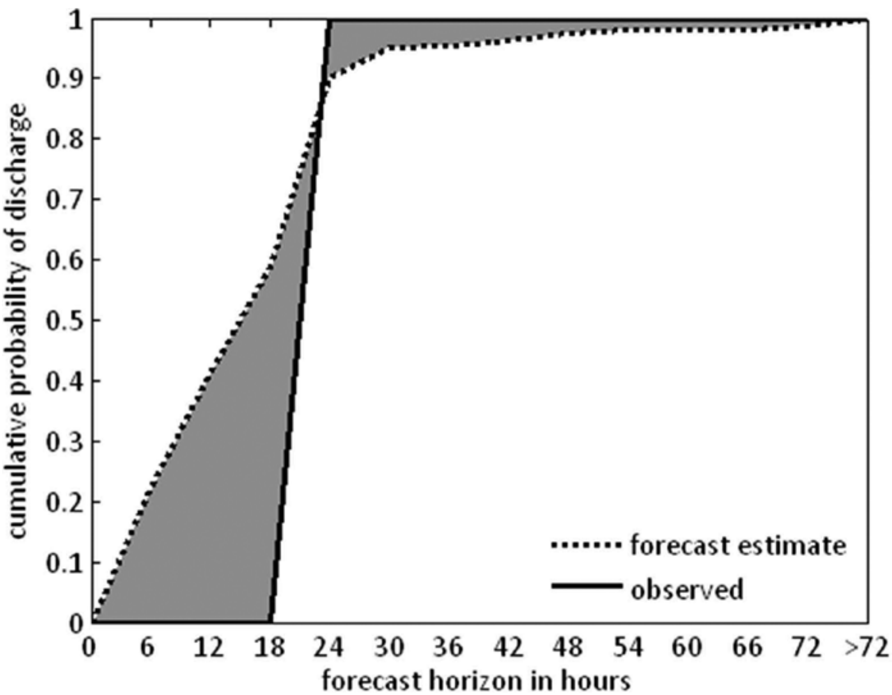

Figure 2. Rank probability score (*gray area*) for example forecast window. *Dotted line*, forecast estimate; *dashed line*, observed.

The order selection objective was to determine the most highly predictive set of orders from the 60 hypothesized to influence LOS. Univariate and forward stepwise analysis was used with the objective of minimizing mean RPS. Fixed predictor variables were initialized in all analysis with univariate and stepwise procedures only conducted on orders. Marginal utility of each final model order was examined with the aim of minimizing orders included (i.e., complexity) while maximizing predictive accuracy.

Cross-validation was used to evaluate the regression model's out-of-sample predictive performance (i.e., mean RPS). Patients were split into 80% training and 20% testing sets. Model parameters were generated from the training set with RPS evaluated against the test set. This process was iterated 100 times to ensure stability of both predictive performance and parameter estimates.

RESULTS

Forecast Estimates. The distribution of PICU LOS was heavily right-skewed with a mean of 3.5 days (95% confidence interval 0.3–19.1) and median of 1.7 days (interquartile range 22.2–3.8). The set of orders most predictive of LOS is seen Table 1. Odds ratios estimating patients' likelihood to remain in the PICU for the next 6 hrs (i.e., first forecast interval) are displayed. Additional orders were predictive, but did not significantly improve model accuracy. All orders evaluated may be seen in Supplemental Appendix 1, Supplemental Digital Content 1, http://links.lww.com/CCM/A501. Predictive orders included were categorized by medication, ventilation, activity, laboratory, diet, foreign body, and ECMO. Predictive power (i.e., magnitude and significance; $p < .05$) of orders was associated with frequency of occurrence and diminished as forecast horizon increased as seen in Supplemental Appendix 2, Supplemental Digital Content 1, http://links.lww.com/CCM/A501.

Fixed variables for patients' age, admission source, and readmission status were predictive and significant through all model intervals. Temporal variables characterizing long-stay patients and time-of-day were similarly significant. Time-of-day estimates demonstrate the much higher likelihood of discharge between noon and 6 pm compared to other times. Bounded medication counts by administration method were most effective in predicting LOS compared to grouping medications by type as seen in Supplemental Appendix 1, Supplemental Digital Content 1, http://links.lww.com/CCM/A501. Ventilation orders for 1) continuous ventilation, 2) bi-level or continuous positive airway pressure, and 3) nightly bi-level or continuous positive airway pressure were highly predictive of remaining in the PICU. Activity orders allowing patients' increased mobility were indicative of a patient becoming ready for discharge. The activated partial thromboplastin time/D-dimer laboratory grouped orders were significant and their frequency (i.e., time from last activated partial thromboplastin time/D-dimer laboratory) distinguishable. Mutually exclusive diet orders for withhold food and clear liquid decreased the likelihood of discharge, whereas formula/human milk and regular diet orders predicted an increased likelihood. Peripheral line–associated orders had a low predictive power, but significantly indicate an increased rate of discharge throughout the forecast horizon. ECMO orders did not demonstrate predictive power because of scarcity, occurring in only 1.1% of patients. However, ECMO orders were highly indicative of remaining in the PICU for this population. If an ECMO-associated order was present, the estimated forecast is superseded by the estimate for this population. The ECMO cumulative estimate was linear ranging from a 0% probability of discharge within 6 hrs to a 10% chance by 3 days. In this fashion, the model is adaptable to orders that are scarce, but are known to be highly predictive.

Model Accuracy. Provider orders were predictive of LOS in real-time accurately forecasting discharge time within a 12-hr window: 46% for patients within 1 day of discharge, 34% for patients within 2 days of discharge, and 27% for patients within 3 days of discharge. To clarify when any patient approaches 2 days from actual discharge time, the forecast model will predict their discharge to be 2 days away with 34% accuracy. Similarly, any patient within 1 day of discharge will be accurately predicted at a rate of 46%. Figure 3 (*left*) displays this same forecast accuracy for all patients by hours from impending discharge time (i.e., order-based model forecast). Accuracy diminishes as patients are further from discharge, likely because of increased severity and uncertainty associated with their health condition. In addition, Figure 3 (*left*) demonstrates how incorporating provider orders (i.e., order-based model) results in a two- to three-fold improvement in accuracy compared to the model solely relying on fixed and temporal predictor variables (i.e., empirical model). The empirical model variables included age, admission source, readmission status, time-of-day, and long-stay (i.e., patient has been present for ≥3 days). A similar 29% improvement in mean RPS across all patients between the order-based (mean RPS = 1.88) and empirical (2.24) model was exhibited. The

Table 1. Forecast model for odds of remaining in the pediatric intensive care unit for next 6 hr horizon

Category	Predictor Variable	Operating Room (95% Confidence Interval)	*p*
Age	Age	0.98 (0.97–0.99)	<.001
Source	*Operating room: Reference*	—	—
	Emergency department	1.53 (1.35–1.74)	<.001
	Intrahospital	1.72 (1.48–2.00)	<.001
	Direct Admission	1.42 (1.24–1.70)	<.001
Readmission	Readmission status	1.45 (1.22–1.74)	<.001
Timing	Long stay (length of stay >3 days)	1.52 (1.37–1.69)	<.001
	Monday: Reference	—	—
	Tuesday	1.02 (0.83–1.25)	.850
	Wednesday	0.77 (0.64–0.93)	.008
	Thursday	0.77 (0.64–0.93)	.007
	Friday	0.81 (0.67–0.98)	.028
	Saturday	0.87 (0.72–1.06)	.163
	Sunday	0.94 (0.77–1.14)	.524
	6 AM to Noon: Reference	—	—
	Noon to 6 PM	0.23 (0.20–0.26)	<.001
	6 PM to Midnight	0.54 (0.46–0.62)	<.001
	Midnight to 6 AM	3.70 (2.8–4.8)	<.001
Medication	Enteral count[a]	0.91 (0.85—0.98)	.016
	Infusion count[b]	2.38 (1.92–2.97)	<.001
	Injection count[c]	1.45 (1.34–1.58)	<.001
Ventilation	Continuous	10.66 (6.25–18.17)	<.001
	Bi-level or continuous positive airway pressure, continuous	7.50 (3.98–14.13)	<.001
	Bi-level or continuous positive airway pressure, nightly	2.09 (1.34–3.25)	<.001
Activity	Activity age appropriate	0.23 (0.20–0.28)	<.001
	Out of bed	0.32 (0.25–0.42)	<.001
Laboratory	Activated partial thromboplastin time/D-dimer (frequency <6 hrs)	11.63 (5.45–10.02)	<.001
	Activated partial thromboplastin time/D-dimer (frequency ≥6 hrs)	4.19 (2.39–7.35)	<.001
	Lactic acid laboratory	10.46 (4.93—22.21)	<.001
Diet	Clear liquid diet	1.83 (1.38–2.41)	<.001
	Formula/human milk	0.67 (0.52–0.87)	.002
	Withhold food	2.24 (1.74–2.88)	<.001
	Regular diet	0.61 (0.51–0.74)	<.001
Foreign Body	Peripheral line	0.67 (0.57–0.81)	<.001
Extracorporeal membrane oxygenation	Extracorporeal membrane oxygenation[d]	—	—

[a]Enteral medication count range: none = 0, low = 1–4, high > 4; [b]infusion medication count range: none = 0, low = 1–2, high > 2; [c]injection medication count range: none = 0, low = 1–9, high > 9; [d]extracorporeal membrane oxygenation orders supersede joint-forecast model when present.

order-based to empirical model comparison was done to explicitly isolate the contribution of provider orders to predictive accuracy within an order-based model that also incorporates fixed and temporal variables. The substantial (i.e., two- to three-fold) improvement in accuracy demonstrates the significance of orders compared to static and temporal information. The calibration curve for the order-based forecast model may also be seen in Figure 3 (*right*). The model was well calibrated demonstrating correspondence between mean forecasted and observed discharge probability throughout the forecast horizon. Cross-validation was used to evaluate out-of-sample predictive performance. Predictive performance (i.e., mean RPS) remained stable varying <20% through all cross-validation procedures.

DISCUSSION

Results suggest that provider orders are useful for real-time prediction of patients' LOS. Orders directly represent provider decision making over time. This captures a portion of information related to patients' changing conditions, making it useful for prediction. Using provider orders for real-time analysis and application is advantageous. First, all information is likely available in real-time with time stamps through a single computerized POE data source. Comparatively, collecting physiological information from multiple data sources (i.e., monitors, electronic medical records, laboratory, radiology) offers more complex data management challenges. Second, orders are naturally generated requiring no additional user input from providers. In busy healthcare environments, applications designed for minimal maintenance are more likely to succeed (33). Lastly, the methods were designed to be generalized to other ICUs and inpatient settings despite varying order patterns and timing of work processes. Models are adaptable in that predictive orders and their parameter estimates may differ, but we hypothesize that orders in most settings provide valuable LOS information.

This study contrasts previous work that generates LOS predictions using demographic, diagnostic, and physiologic measures (23–26). However, no conclusions can be drawn about the accuracy of order-based forecast models compared to previously developed physiological-based (e.g., Acute Physiology and Chronic Health Evaluation) models. Although a potentially useful future investigation, a direct comparison is not easily interpreted because physiologic-based models have differing primary objectives and typically make one-time predictions on or near arrival. Our objective is distinct in attempting to capture real-time updates in patients' conditions and project LOS onward. Probabilistic forecasts were well-suited for this task, given the variability associated with patients' conditions and hospital work processes. Probability forecasts also allow for easy aggregation and determination of bed availability. For example, if five patients each have a 20% chance of being discharged between 12 and 18 hrs, one bed is likely to become available during that future time interval. This concept is valuable to bed management personnel (e.g., charge nurses, intensivists) because understanding health condition and projecting discharge for a large number of patients in a unit require significant information gathering. Aggregate comprehension of this information and translation toward projections of bed availability require a high degree of cognition. A probabilistic forecast driven from naturally generated orders is intended to automatically support information gathering and aggregate comprehension for patient flow projections. Probabilistic forecasts are useful for many healthcare applications, but methods for accuracy evaluation stem from the fields of meteorology and financial risk

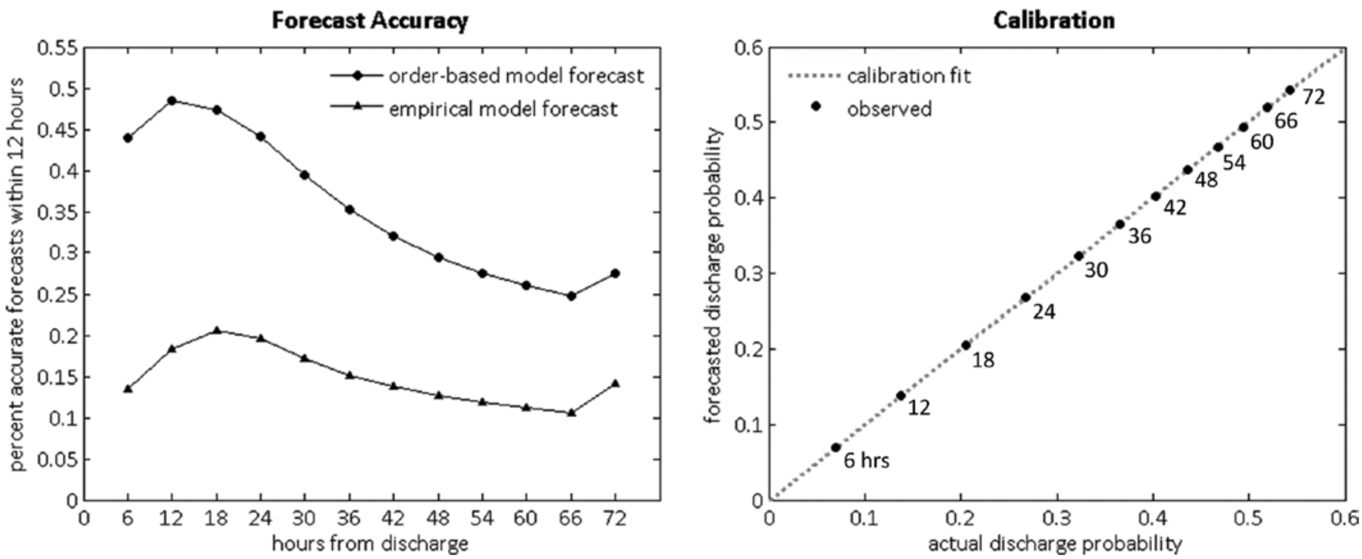

Figure 3. Forecast model accuracy within a 12-hr window (*left*) and calibration (*right*). *Dotted lines*, calibration fit; *filled circle*, observed; *filled rhombus*, observed-based model forecast; *filled triangle*, empirical model forecast.

management (32, 34). However, accuracy will ultimately be evaluated by application end users, and their trust in allowing it to support patient flow decisions. Effective support may include quickly and automatically placing evidence (i.e., clinician confidence) behind projections and patient flow decisions routinely made. Support may also entail altering decisions for improved patient flow management based on more accurate and longer time horizon forecasts.

There are several limitations to this research application. Forecast accuracy is highly dependent on the reliability and timeliness of order placement. Orders placed electronically to affect a desired response (e.g., laboratory, medication) are likely reliable. However, other computerized POE information may not be. For example, we aimed to track ventilation by initiation (i.e., intubation) and discontinue (i.e., extubation). However, many patients arrive to the PICU already on ventilators and the extubation order was not consistently used. We elected to monitor any order associated with being ventilated or altering settings as a surrogate method of tracking. Forecast models are able to accommodate uncertainty associated with order information and translate this probabilistically. In addition, we know that many types of orders are indicative of LOS. Targeting a subset orders most frequently and consistently entered will be most effective in making accurate predictions. Limitations exist in the handling of patients who die in-hospital. These patients have been excluded from our model development cohort. An applicable prospective cohort would include these patients because in-hospital mortality and time of death are unknown. However, our forecast model does not significantly change when including patients who die likely because they comprise a small (3.2%) proportion of all patients in the PICU. The model is likely to change and exhibit decreases in accuracy for cohorts (i.e., hospital units) where mortality rates are higher. Future work to externally validate the forecast model in other PICUs, and eventually other types of hospital units, is needed to prove generalizability. A limitation of this study is that we have only internally validated our forecast model. We hypothesize that different sets of predictive orders may emerge in other inpatient units and forecast accuracy will vary. However, we believe the methods of model development and forecasting will effectively generalize. Other limitations exist in interpreting the meaning of the accuracy measures. It is unknown what level of accuracy is required to support user decision making. Implementation of the forecast application and evaluating its use are the only true means of determining accuracy requirements.

CONCLUSIONS

Provider orders reflect dynamic changes in patients' conditions making them useful for real-time LOS prediction. This study demonstrates the development and evaluation of a continuously updated LOS forecast model driven by computerized provider orders. Providing accurate and timely LOS forecasts to key personnel may support improved management of patient flow through ICUs and hospitals. Deploying systems engineering tools as informatics applications provides the ability to leverage naturally generated clinical information to perform more evidence-based management of ICU resources.

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