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Is patient length of stay associated with intensive care unit characteristics?

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ABSTRACT

Purpose: We described the association between Intensive care units (ICU) characteristics and ICU Length of stay (LoS), after correcting for patient characteristics. We also compared the predictive performances of models including either patient and ICU characteristics or only patient characteristics.
Materials and methods: We included all admissions of 38 ICUs participating in the Dutch National Intensive Care Evaluation registry (NICE) between 2014 and 2016. We performed mixed effect regression including, one ICU characteristic in each model and a random intercept per ICU. Furthermore, we developed a prediction model containing multiple ICU characteristics and patients characteristics.
Results: We found negative associations for the number of hospital beds; number of ICU beds; availability of fellows in training for intensivist; full-time equivalent ICU nurses; and discharged in a shift with 100% bed occupancy. Furthermore, we found a U-shaped association with the nurses to patient ratio as spline function. The performance based on R^2 was between 0.30 and 0.32 for both the model containing only patient characteristics and the model also containing ICU characteristics.
Conclusion: After correcting for patient characteristics, we found statistically significant associations between ICU LoS and six ICU characteristics, mainly describing staff availability. Furthermore, we conclude that including ICU characteristics did not significantly improve ICU LoS prediction.

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1. Introduction

Intensive care units (ICUs) provide complex and expensive care and hospitals face pressure to improve efficiency and reduce costs [1,2]. Since costs are strongly related to ICU length of stay (LoS), shorter ICU LoS generally equates to lower costs [2-4]. ICU LoS is associated with patients' severity of illness [5-7] and hence case-mix adjustment is important when analyzing and modeling LoS.

Previously, we defined three main reasons for modeling ICU LoS [6]. These were: 1) planning the number of beds and members of staff required to fulfil demand for ICU care within a given hospital or geographical area; 2) identifying individual patients or groups of patients with unexpectedly long ICU LoS to drive direct quality improvement; and 3) comparing LoS between ICUs when benchmarking. Although a range of models for predicting ICU LoS using patient characteristics have been published, the clinical utility of these models for these purposes is suboptimal [6]. One reason for the suboptimal nature of these models may be the difficulty of approximating ICU LoS using standard statistical distributions [5].

In a previous study we aimed to predict individual patient LoS for benchmarking purposes by regression methods using patient characteristics at admission time only and concluded that it is difficult to predict ICU LoS [5]. We hypothesize that information on ICU characteristics is required to model ICU LoS for an individual ICU accurately.

Previous studies discussed the association between ICU LoS and among others the number of ICU and hospital beds [8,9]; the availability of step down or intermediate units [10,11]; intensivist to bed ratios [12]; the presence of full-time intensivists [13,14]; presence of fellows [15]; type of hospital [8,13,16-18]; types of care protocol [10,17,19]; and having clear admission and discharge policies [10]. Additional research has been performed on modeling ICU bed shortages [20,21], but not on direct associations with ICU LoS. However, not all these studies correct for patient characteristics as a base prior to analyse the association between ICU LoS.

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Our primary aim is to describe associations between ICU characteristics and ICU LoS, correcting for patient characteristics. We also compare the predictive performance of a model including patient and ICU characteristics and one including only patient characteristics [6] for ICU LoS. We used data collected in the Dutch National Intensive Care Evaluation (NICE) registry [22].

2. Material and methods

2.1. The Dutch National Intensive Care Evaluation registry

The NICE registry exists since 1996 and collects data on patient characteristics, such as demographics, physiological and diagnostic data [22]. In addition, the registry records ICU characteristics and quality indicators for a subgroup of voluntary participating ICUs. Twice a year these ICUs report to the registry on staff resources, hospital type, ICU level, and the number of beds available. Four times a year they report on the availability of intensivists and policies to reduce the risk of medication errors. Every shift (day, evening, night), they report on availability of ICU nurses and operational ICU beds. The medical ethics committee of the Academic Medical Center stated that medical ethics approval for this study was not required under Dutch law (registration number W16_314).

2.2. Study data

We included ICUs, for which patient level information and characteristics recorded per shift was available for at least 23 complete months between January 1st, 2014 and January 1st, 2016 and the ICU characteristics recorded twice or four times a year were available and judged to be reliable by one of the authors (IV). ICU characteristics recorded twice a year or quarterly rarely change, since staff resources, hospital type, ICU level and number of available beds generally remain stable. We chose to use data on 2015 or the most recent data. We merged yearly and quarterly data on the ICUs to the patient record level data, using ICU as the merge variable. The maximum two records recorded for the half yearly data and four records recorded for the quarterly data were averaged to combine them into one record. Data recorded for each shift were merged to patient level data if the shift overlaps the patient admission period. ICU characteristics available on a shift level were averaged over the patients' admission period. We present a flow chart of ICU and patient inclusions in Fig. 1.

2.3. Identification of ICU characteristics for inclusion in the regression analysis

To identify ICU characteristics for inclusion in the regression analysis an intensivist (DD) identified ICU characteristics recorded in the NICE registry, which he thought would have a clinically relevant association with ICU LoS. We supported this work with a snowball literature search to identify ICU characteristics with an indication of association with ICU LoS. We examined potential collinearity by calculating Pearson's correlation coefficients between pairs of ICU characteristics. Collinearity occurs if two predictors are highly linearly related. We defined collinearity if the correlation coefficient was smaller than −0.9 or larger than 0.9.

2.4. Statistical analysis

To examine the shape of the association between individual ICU characteristics and ICU LoS we used stacked histograms (Fig. S1) and scatterplots. The patient and ICU characteristics examined are respectively presented in Tables 1 and 2. We found a U-shaped relationship between ICU LoS and nurse-to-patient ratio, presented in Fig. 2, and included it as spline, with four degrees of freedom in the regression models.

For each individual ICU characteristic we performed a mixed-effects ordinary least square regression with a random intercept per ICU and log-transformed ICU LoS as the dependent variable [5]. A block of patients' characteristics and for each model one ICU characteristic were included as fixed-effects. There were two steps in our model building strategy. In the first step, we included the patient characteristics identified in a previous publication [5]. The model was subsequently simplified using stepwise backward selection and the Akaike Information Criterion (AIC) and the corresponding p-value based on the likelihood ratio test to test model improvement and used p-value > 0.01 for exclusion. We viewed the patient characteristics in the resulting model as a fixed block of variables to be included in all further models. In the second step, we included the fixed block of patient case-mix characteristics and one ICU characteristic as fixed covariates and a random intercept for each ICU. We compared each model to the model with only patient characteristics by computing analysis of deviance tables and using the chi-squared distribution to compare them. We defined improvement as a p-value smaller than 0.05 [23].

To examine the potential improvement of a prediction model for log-transformed ICU LoS using both patient and ICU characteristics compared to a model correcting for patient characteristics only we performed another mixed effect regression analysis. We performed stepwise backward selection as described above starting with all ICU characteristics with p-value larger than 0.1 to exclude ICU characteristics. We included the patient characteristics as a fixed block of variables. We compared the difference in the residual deviances of the models to a chi-squared distribution as described above.

The models' performance was examined by analyzing statistics of the residuals of both models and deriving R^2 on a patient level using a general method for obtaining R^2 for mixed-effect models [24]. Finally, we evaluated the performance by presenting a recalibration plot of 50 subgroups based on the mean predicted log-transformed ICU LoS based on fixed-effects only. For each subgroup we plot the mean predicted log-transformed ICU LoS against the mean observed log-transformed ICU LoS.

We performed all statistical analyses using R statistical software, version 3.3.1 (R Foundation for Statistical Computing, Vienna, Austria) [25]. We used the lme4 package for mixed-effects models [26] and rms package for calculating restricted cubic splines [27].

3. Results

3.1. Identification of ICU characteristics for inclusion in the regression analysis

Supplementary Table S1 shows all ICU characteristics included in the analyses and identified as being clinically associated with ICU LoS. Table S2 presents the Pearson correlation coefficients between these variables. No pairs of ICU characteristics demonstrated collinearity, hence we included all variables in the univariate analyses.

3.2. Study data

A total of 84 ICUs participated in the NICE registry between January 1st, 2014 and January 1st, 2016. Of these, 54 (64%) participated in the ICU characteristics and quality indicator registration. We included 38 (70%) in this study. The remaining 16 ICUs provided unreliable data on one or more of the ICU characteristics examined in this paper. We included 93,807 ICU admissions, of which we included 78,822 (84%) in this study, Fig. 1. Tables 1 and 2 respectively present information about the number of admissions and ICU LoS for each of the patient characteristics and each of the ICU characteristics.

3.3. Statistical analysis

We removed two variables from the block of patient characteristics during the backwards selection procedure. These were hematologic

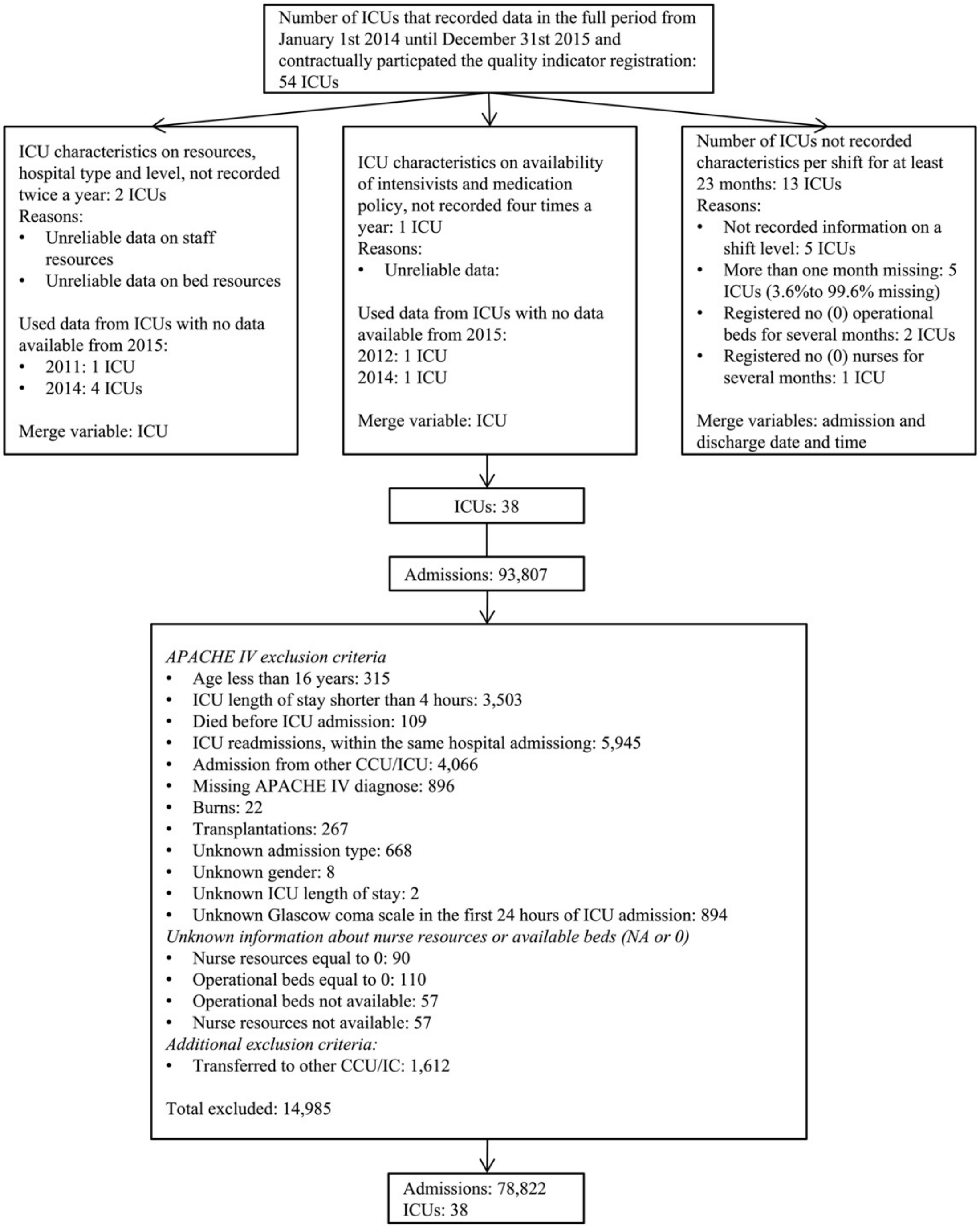

Fig. 1. Flow diagram of ICU and patient inclusion.

malignity ($p = 0.887$) and chronic obstructive pulmonary disease ($p = 0.162$). Table 1, contains the patient characteristics used in the model and Table S3 presents the results of the regression analyses for patient characteristics. In Table 3, we present the results of the regression analyses for individual ICU characteristics. Six demonstrated a statistically significant association with ICU LoS: number of hospital beds; number of ICU beds; availability of fellows in training for intensivist; full-time equivalent ICU nurses; whether a patient was discharged in a shift with 100% bed occupancy; and nurse to patient ratio. Apart from the nurse to patient ratio, all characteristics had a negative association with ICU LoS.

Examining the potential improvement of a model for log-transformed ICU LoS by including ICU characteristics resulted in a model with number of ICU beds; full-time equivalent ICU nurses; and whether a patient was discharged in a shift with 100% bed occupancy, Table 3. The fit statistics in Fig. S2, presents the performance of the model with correction for case-mix characteristics and ICU characteristics. Comparing the performance of this full model with the model with only patient case-mix included, lead to R^2 between 0.30 and 0.32 for both models. Furthermore, residuals showed biased results for patients with short and long ICU LoS, but followed a normal distribution overall. Fig. S3, presents a calibration plot comparing predicted and observed values for 50 subgroups based on mean predicted log-transformed ICU LoS. For the model including ICU characteristics, we found that the total predicted ICU LoS was slightly closer to the total observed values and that ICU level differences were associated with the number of ICU nurses available.

Table 1
Patient characteristics included in the model.

Patient case-mix characteristic	Patients with patient Characteristic (yes)		Patients without patient characteristic (no)
	Admission count (%)	Mean (sd) ICU length of stay in days	Mean (sd) ICU length of stay in days
Number of ICU admissions	78,822	3.1 (6.6)	
Age in years[a]			
Up to 55	20,866 (26)	2.9 (6.3)	
56 to 66	19,938 (25)	3.3 (7.1)	
67 and 74	18,498 (23)	3.3 (6.8)	
Over 74	19,520 (25)	3.2 (6.2)	
Gender male	47,309 (60)	3.2 (6.9)	1.3 (2.2)
Admission type			
Medical	35,646 (45)	4.1 (7.5)	
Urgent surgery	9203 (12)	4.7 (9.2)	
Elective surgery	33,973 (43)	1.7 (3.9)	
APACHE IV physiology score (APS) (quartiles)[a]			
Up to 26	20,366 (26)	1.3 (2.2)	
26 to 38	19,831 (25)	1.9 (3.6)	
38 to 56	18,979 (24)	3.3 (6.3)	
Over 56	19,646 (25)	6.2 (10.2)	
Confirmed infection	11,501 (15)	6.2 (10)	2.6 (5.7)
Mechanical ventilation during the first 24 h of admission	37,809 (48)	4.5 (8.5)	1.9 (3.8)
Vasoactive drug use first 24-h of admission	32,766 (42)	4.6 (8.6)	2.1 (4.5)
Lowest Glasgow coma score < 15 first 24 h of admission	16,205 (21)	4.9 (8.7)	2.7 (5.9
Chronic diagnoses			
Cardio vascular insufficiency	3698 (5)	3 (5.7)	3.2 (6.6)
Chronic renal insufficiency	4370 (6)	3.8 (7.0)	3.1 (6.6)
Chronic dialysis	1089 (1)	2.8 (4.9)	3.2 (6.6)
Cirrhosis	1110 (1)	4.2 (6.6)	3.1 (6.6)
Chronic obstructive pulmonary disease (COPD)[b]	11,014 (14)	3.6 (6.6)	3.1 (6.6)
Diabetes	13,265 (17)	3.3 (6.6)	3.1 (6.6)
Hematologic malignancy[b]	1277 (2)	5.5 (8.7)	3.1 (6.5)
Immunologic insufficiency	6803 (9)	4.2 (7.8)	3.0 (6.5)
Neoplasm	3811 (5)	2.6 (5.1)	3.2 (6.7)
Respiratory insufficiency	3361 (4)	4.7 (8.4)	3.1 (6.5)
Acute diagnoses			
Acute renal failure	6196 (8)	7.1 (11.4)	2.8 (5.9)
Cardiopulmonary reanimation (CPR)	3391 (4)	5.7 (9.0)	3.0 (6.4)
Cerebrovascular accident (CVA)	3238 (4)	4.8 (7.7)	3.1 (6.5)
Dysrhythmia	5970 (8)	4.9 (8.3)	3.0 (6.4)
Gastro intestinal bleeding	1574 (2)	2.8 (5.8)	3.2 (6.6)
Intracranial mass effect	3950 (5)	4.6 (9.7)	3.1 (6.4)
APACHE IV admission diagnose (head categories)			
Cardiovascular non-operative	11,611 (15)	4.3 (7.5)	
Cardiovascular operative	20,957 (27)	2.4 (5.7)	
Gastro-intestinal non-operative	2697 (3)	3.4 (6.7)	
Gastro-intestinal operative	7318 (9)	2.8 (5.4)	
Genito-urinary non-operative	981 (1)	3.2 (5.2)	
Genito-urinary operative	2090 (3)	1.5 (2.9)	
Hematology non-operative and operative	358 (0)	4.3 (7.2)	
Metabolic non-operative	1219 (2)	2.1 (3.6)	
Metabolic operative	188 (0)	1.8 (3.7)	
Musculoskeletal/skin non-operative	149 (0)	4.6 (9.1)	
Musculoskeletal/skin operative	1699 (2)	1.4 (2.4)	
Neurological non-operative	6689 (8)	2.9 (6.5)	
Neurological operative	4651 (6)	2.2 (4.9)	
Respiratory non-operative	9590 (12)	5.3 (8.5)	
Respiratory operative	4198 (5)	1.8 (4.4)	
Transplant operative	406 (1)	2.4 (3.6)	
Trauma non-operative	2348 (3)	3.8 (7.7)	
Trauma operative	1673 (2)	4.1 (11.9)	
Outcome measure			
ICU death: yes	6150 (8)	5.8 (10.6)	2.9 (6.1)
Hospital death	8878 (11)	5.7 (10.0)	2.8 (6.0)

[a] Continuous variables age and APACHE IV physiology score (APS) are presented in quartiles, but they were included as splines in the regression analyses.
[b] COPD and hematological malignancy were removed from the model during backward selection.

4. Discussion

In this study, we examined the association between ICU characteristics available in the NICE registry and ICU LoS, after correcting for patient characteristics. The results of our study show statistically significant associations for the number of hospital beds; the number of ICU beds; full-time equivalent ICU nurses; whether fellows in training for intensivist were available; nurse to patient ratio; and whether a patient was discharged in a shift with 100% bed occupancy. Adding these characteristics to a

Table 2
Summary of included ICU characteristics.

ICU characteristics[a,b]	Admission count (%)	Number of ICUs	Mean (sd) length of stay
ICU level			
1	9854 (13)	11	2.6 (5.1)
2	20,756 (26)	13	3.3 (6.7)
3	48,212 (61)	14	3.2 (6.8)
Hospital type			
University affiliated	20,569 (26)	5	3.3 (7.2)
Teaching	36,411 (46)	15	3.1 (6.5)
General	21,842 (28)	18	3.1 (6.1)
Number of hospital beds (25% percentiles)			
Up to 382	12,992 (16)	10	2.7 (5.5)
383 to 482	12,743 (16)	9	3.6 (6.8)
483 to 660	17,779 (23)	9	3.3 (7)
Over 660	35,308 (45)	10	3.1 (6.6)
Number of ICU beds (25% percentiles)			
Up to 8	8675 (11)	10	2.5 (4.7)
9 to 12	6633 (8)	5	3.2 (6.9)
13 to 21	23,091 (29)	13	3.4 (6.8)
Over 21	40,423 (51)	10	3.1 (6.8)
Stepdown beds with supervision: no	41,249 (52)	23	3.1 (6.2)
Stepdown beds with supervision: yes	37,573 (48)	15	3.2 (7)
Stepdown beds without supervision: no	66,670 (85)	34	3.2 (6.7)
Stepdown beds without supervision: yes	12,152 (15)	4	2.8 (5.9)
PACU beds with mechanical ventilation: no	54,799 (70)	31	3.1 (6.3)
PACU beds with mechanical ventilation: yes	24,023 (30)	7	3.3 (7.1)
PACU beds without mechanical ventilation: no	59,148 (75)	28	3 (6.2)
PACU beds without mechanical ventilation: yes	19,674 (25)	10	3.5 (7.7)
CCU beds: no	70,406 (89)	34	3.1 (6.5)
CCU beds: yes	8416 (11)	4	3.5 (7.2)
Calamity beds: no	29,290 (37)	12	3 (6.4)
Calamity beds: yes	49,532 (63)	26	3.2 (6.7)
Medication error prevention score			
6	1936 (2)	1	3.6 (6.2)
7	18,635 (24)	7	3.4 (7.5)
8	38,614 (49)	20	3 (6.2)
9	13,559 (17)	8	3.2 (6.1)
10	6078 (8)	2	3.5 (7)
Fellows in training to intensivist available: no	55,491 (70)	32	3.1 (6.4)
Fellows in training to intensivist available: yes	23,331 (30)	6	3.3 (7.1)
Full-time equivalent ICU doctors (non-intensivists)			
Up to 3.0	11,242 (14)	9	3.2 (6.3)
3.0 to 6.0	10,059 (13)	7	3.1 (6.8)
6.0 to 8.8	21,526 (27)	12	3.1 (6.6)
Over 8.8	35,995 (46)	10	3.2 (6.7)
Full-time equivalent ICU nurses			
Up to 6.5	10,269 (13)	23	2.6 (4.9)
6.5 to 10.9	11,285 (14)	26	3.1 (6.2)
10.9 to 17	19,145 (24)	26	3.4 (6.8)
Over 17	38,123 (48)	20	3.2 (7)
Full-time equivalent intensivists			
Up to 4.3	11,861 (15)	10	3.2 (6.3)
4.3 to 5.1	13,327 (17)	9	2.9 (6)
5.1 to 7.0	18,962 (24)	9	3.2 (6.6)
Over 7.0	34,672 (44)	10	3.2 (6.9)
Nurses to patient ratio			
Up to 0.6	20,579 (26)	38	2.7 (5.7)
0.6 to 0.7	19,266 (24)	38	3.6 (7.5)
0.7 to 0.8	19,025 (24)	38	3.5 (7.5)
Over 0.8	19,952 (25)	38	2.8 (5.5)
Intensivists to operational beds ratio			
Up to 0.3	25,872 (33)	9	3.1 (6.6)
0.3 to 0.4	15,209 (19)	10	3.2 (6.5)
0.4 to 0.5	18,844 (24)	9	2.8 (5.7)
Over 0.5	18,897 (24)	10	3.5 (7.5)
Hours intensivist present			
Up to 15	10,109 (13)	10	3.2 (6.3)
15 to 17	15,183 (19)	9	3.7 (7.9)
17 to 22	24,624 (31)	9	3 (6.1)
Over 22	28,906 (37)	10	3 (6.3)
Discharged in shift with 100% bed occupancy: no	63,836 (81)	38	3.1 (6.4)
Discharged in shift with 100% bed occupancy: yes	14,986 (19)	37	3.2 (7.2)

ICU = intensive care unit, PACU = post anesthesia care unit, CCU = coronary care unit.
[a] Continues characteristics included as continuous or spline covariates are presented using center level quartiles. For the characteristic full-time equivalent ICU nurses and nurses to patient ratio patient level quartiles were used, since this characteristic was recorded per shift.
[b] We included variables on numbers of specific bed types and number of fellows in training to intensivist to include as binary covariates in the analyses. Specific bed types were not available and among ICUs with availability of such beds the number of beds we found that it was often just one or two beds.

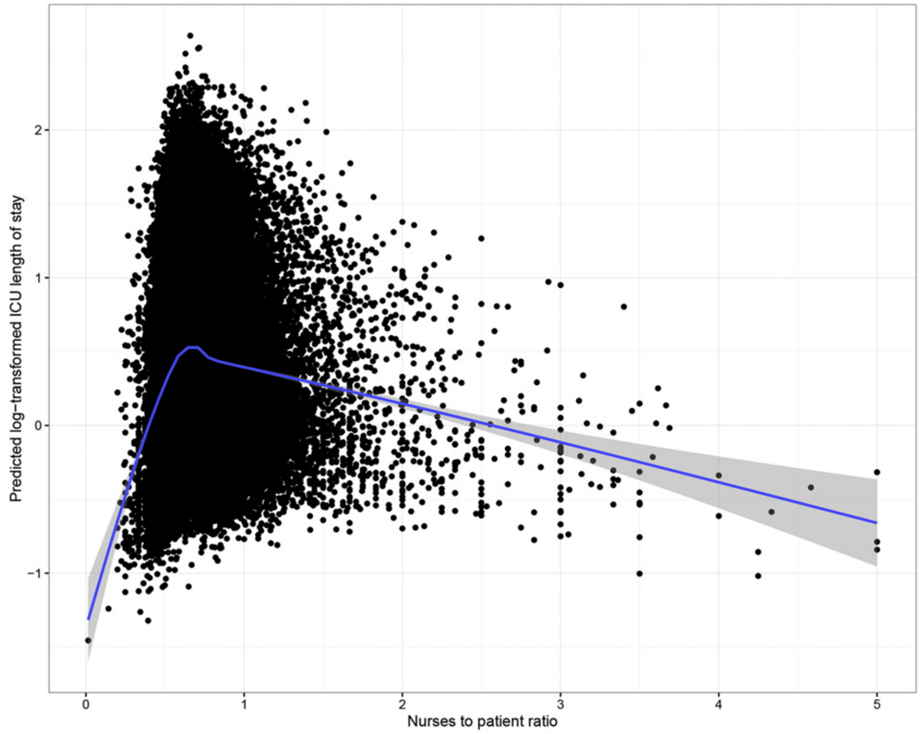

Fig. 2. Predicted log-transformed ICU length of stay by nurses to patient ratio. Log-transformed ICU length of stay is adjusted for patient case-mix characteristics and nurses to patient ratio included as spline. A smoothing curve was derived using generalized additive model method. Grey zones represent 95% confidence intervals.

multivariate prediction model with patient characteristics did not improve the performance of the model. We hypothesized that case-mix corrected ICU LoS is associated with these characteristics. Hence, our data show that adding ICU characteristics will not substantially improve predictive performance for planning beds and staff requirements, identifying patients with unexpected long LoS or benchmarking ICUs.

We found that as the numbers of hospital or ICU beds increase ICU LoS decreases. A previous study found no associations between ICU LoS and number of hospital beds in five categories after case-mix

Table 3
Coefficients for ICU characteristics in the mixed effects regression models.

Characteristics	Models including a single ICU characteristic		Final model including multiple ICU characteristics	
	Parameter (95% CI)	p-Value	Parameter (95% CI)	p-Value
ICU level (reference 1 (lowest))		0.803		
2	0.030 (−0.088 to 0.150)			
3 (highest)	−0.003 (−0.119 to 0.110)			
Hospital type (reference general hospital)		0.093**		
Teaching hospital	−0.048 (−0.143 to 0.047)			
University affiliated	−0.148 (−0.285 to −0.012)			
Number of hospital beds / 100	−0.017 (−0.034 to 0.001)	0.040*		
Number of ICU beds / 10	−0.045 (−0.09 to −0.002)	0.039*	0.009 (0.002 to 0.014)	<0.001
Stepdown beds with supervision: yes	−0.031 (−0.124 to 0.063)	0.512		
Stepdown beds without supervision: yes	−0.049 (−0.198 to 0.100)	0.509		
PACU beds with mechanical ventilation: yes	−0.068 (−0.184 to 0.048)	0.242		
PACU beds without mechanical ventilation: yes	0.033 (−0.071 to 0.137)	0.522		
CCU beds: yes	0.008 (−0.142 to 0.159)	0.912		
Calamity beds: yes	0.037 (−0.062 to 0.135)	0.456		
Fellows in training to intensivist available: yes	−0.145 (−0.261 to −0.035)	0.016*		
Full-time equivalent ICU doctors (non-intensivists)	−0.004 (−0.011 to 0.003)	0.227		
Full-time equivalent ICU nurses	−0.017 (−0.021 to −0.013)	<0.001*	−0.030 (−0.034 to −0.025)	<0.001
Full-time equivalent intensivists	−0.010 (−0.021 to 0.000)	0.058**		
Intensivists to operational beds ratio	0.000 (−0.317 to 0.32)	0.999		
Nurses to patient ratio (npr) (spline)[a]		<0.001*		
Hours intensivist present	−0.005 (−0.014 to 0.003)	0.221		
Discharged in a shift with 100% bed occupancy	−0.054 (−0.071 to −0.037)	<0.001*	0.035 (0.017 to 0.054)	<0.001
Medication error prevention score	0.001 (−0.054 to 0.056)	0.965		
ICU admission in weekend	−0.004 (−0.021 to 0.013)	0.668		

The coefficients represent the change in log transformed intensive care unit length of stay associated with the characteristic.
ICU = intensive care unit, CI = confidence interval, PACU = post anesthesia care unit, CCU = coronary care unit.
* $p < 0.05$ significant.
** Inclusion in a multivariate model was based on $p < 0.1$. Using stepwise backward selection $p > 0.1$ was used for exclusion.
[a] A graphical result is shown in Fig. 2. 2.573·npr-28.358 (npr-0.491)^3 + 64.672·(npr-0.627)^3 − 36.508·(npr-0.735)^3 − 0.193 (npr-1.061)^3.

adjustment [8]. An explanation could be that larger hospitals care for more severely ill patients. Another study found no change in ICU LoS reducing the number of ICU beds and when severity of illness stayed constant [9]. One of the explanations could be the increase in nurses per bed. We also found that the availability of fellows resulted in an increase of ICU LoS. Previously, ICU LoS has been shown to be longer [15], unaffected [28] or shortened [29] at pediatric ICUs after correcting for patient case-mix in the presence of fellows. Furthermore, we found that the ICU LoS increased as the number of ICU nurses decreased. This conforms a systematic literature review which indicates that the presence ICU nurses is associated with reduced ICU LoS [30]. We found no association between ICU LoS and the ratio of intensivists to operational beds, but the ICU LoS was associated with the ratio of nurses to patients. A previous study has shown that an increase in the bed to physician ratio was associated with a decrease in ICU LoS [12]. One study developed a quality indicator for ICU LoS and classified ICUs in two groups based on efficiency [31]. They analyzed the association between efficiency and ICU characteristics. They found a significant negative association for the number of physicians, intensivist per bed and the availability of intensivist. They found a significant positive association for nurses to bed ratio. However, these associations were not significant in a multivariate model.

We found that ‘discharged in a shift with 100% bed occupancy’ was associated with shorter ICU stay. The reason could be that there was pressure to discharge patients somewhat faster to make bed capacity available. This is in line with previous research, which showed that delays in discharging patients from the ICU decreased when bed occupancy increased [32] and in the event of bed shortage admissions and discharges are triaged, increasing the number of rejected admission requests and shortening the LOS [21,33].

Step-down units are intermediate levels of care between ICU and general wards [10,34]. The availability of step-down units may reduce ICU LoS [11,17,19]. Step-down units were available among the top 10 performing ICUs in United States [10]. We found no association between the availability of step-down beds on the ICU and ICU LoS in our data. However, the NICE registry only records the number of step-down beds under responsibility of an intensivist. Previously, researchers have reported that having a full time intensivist [13,14] or being able to call an intensivist [35] decreases ICU LoS and the absence of a full time intensivist prolonged ICU LoS [36]. Furthermore, studies found that teaching hospitals had longer [8,16,17] or shorter [13,18] ICU LoS. However, following correction for patient characteristics, we found no statistically significant associations between ICU LoS and the average hours of intensivist availability, the availability of intensivists on weekdays or at weekends, the ability to call an intensivist, type of hospital or ICU level.

A strength of this study is the large amount of patient level data available in the NICE registry. Although not all Dutch ICUs register data on their structure and logistics processes, we believe that the ICUs included in this study were representative for all Dutch ICUs as we found similar distribution of ICU level and hospital type among the included and excluded ICUs. A limitation of this study is that we did not have information on the availability of intermediate care or step-down units in the hospitals or on other factors, which may be associated with ICU LoS. These include whether ICUs: had open or closed management models [37-39]; standardized care by following guidelines [17,19] using clinical pathways [17] or process related guidelines and protocols [10,17]; or had discharge policies for when ICU or general beds are scarce. Discharge policies may influence ICU LoS predictions, but may not directly mean low utility in terms of identifying outliers [7]. Another limitation of this study is that although, none of the ICU characteristics showed a correlation coefficient smaller than −0.9 and larger than 0.9 which were chosen as cut-off values for collinearity, it is likely that several characteristics are not independent predictors. For example, the number of ICU beds and the total number of ICU nurses were related. Interestingly, both the number of ICU beds and number of ICU nurses appeared to be independent predictors in multivariate analysis. Furthermore, the direction of the regression coefficient changed for both the number of ICU beds and the 100% bed occupancy, which may be caused by associations between the three ICU characteristics included in the full model. Since the purpose of the full model was to predict ICU LoS, including these correlated ICU characteristics is not a problem.

5. Conclusions

After correcting for patient characteristics, we found statistically significant associations between ICU LoS and six ICU characteristics. These characteristics mainly describe staff availability. Adding ICU characteristics to a prediction model for ICU LoS already containing patient characteristics did not substantially improve the performance of the model. This indicates that the use of ICU characteristics have little additional utility above the use of only patient characteristics, when predicting ICU LoS.

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References

[1] Halpern NA, Pastores SM. Critical care medicine beds, use, occupancy, and costs in the United States: a methodological review. Crit Care Med 2015;43(11):2452–9.
[2] Halpern NA, Pastores SM, Greenstein RJ. Critical care medicine in the United States 1985–2000: an analysis of bed numbers, use, and costs. Crit Care Med 2004;32(6):1254–9.
[3] Halpern NA, Pastores SM, Thaler HT, Greenstein RJ. Critical care medicine use and cost among Medicare beneficiaries 1995–2000: major discrepancies between two United States federal Medicare databases. Crit Care Med 2007;35(3):692–9.
[4] Kahn JM, Rubenfeld GD, Rohrbach J, Fuchs BD. Cost savings attributable to reductions in intensive care unit length of stay for mechanically ventilated patients. Med Care 2008;46(12):1226–33.
[5] Verburg IW, de Keizer NF, de Jonge E, Peek N. Comparison of regression methods for modeling intensive care length of stay. PLoS One 2014;9(10):e109684.
[6] Verburg IWM, Atashi AES, Holman R, Abu-Hanna A, de Jonge E, de Keizer NF. Which models can I use to predict adult ICU length of stay? A systematic review. Crit Care Med 2017;45(2):222–31.
[7] Straney LD, Udy AA, Burrell A, Bergmeir C, Huckson S, Cooper DJ, et al. Modelling risk-adjusted variation in length of stay among Australian and New Zealand ICUs. PLoS One 2017;12(5):e0176570.
[8] Knaus WA, Wagner DP, Zimmerman JE, Draper EA. Variations in mortality and length of stay in intensive care units. Ann Intern Med 1993;118(10):753–61.
[9] Walther SM, Jonasson U. Outcome of the elderly critically ill after intensive care in an era of cost containment. Acta Anaesthesiol Scand 2004;48(4):417–22.
[10] Zimmerman JE, Alzola C, Von Rueden KT. The use of benchmarking to identify top performing critical care units: a preliminary assessment of their policies and practices. J Crit Care 2003;18(2):76–86.
[11] Adamski J, Goraj R, Onichimowski D, Gawlikowska E, Weigl W. The differences between two selected intensive care units located in central and northern Europe - preliminary observation. Anaesthesiol Intensive Ther 2015;47(2):117–24.
[12] Dara SI, Afessa B. Intensivist-to-bed ratio: association with outcomes in the medical ICU. Chest 2005;128(2):567–72.
[13] Gruenberg DA, Shelton W, Rose SL, Rutter AE, Socaris S, McGee G. Factors influencing length of stay in the intensive care unit. Am J Crit Care 2006;15(5):502–9.

[14] Oliveira AB, Dias OM, Mello MM, Araujo S, Dragosavac D, Nucci A, et al. Factors associated with increased mortality and prolonged length of stay in an adult intensive care unit. Rev Bras Ter Intensiva 2010;22(3):250–6.
[15] Higgins TL, McGee WT, Steingrub JS, Rapoport J, Lemeshow S, Teres D. Early indicators of prolonged intensive care unit stay: impact of illness severity, physician staffing, and pre-intensive care unit length of stay. Crit Care Med 2003;31(1):45–51.
[16] Asano EF, Rasera Jr I, Shiraga EC. Cross-sectional study of variables associated with length of stay and ICU need in open Roux-En-Y gastric bypass surgery for morbid obese patients: an exploratory analysis based on the Public Health System administrative database (Datasus) in Brazil. Obes Surg 2012;22(12):1810–7.
[17] Rosenberg AL, Zimmerman JE, Alzola C, Draper EA, Knaus WA. Intensive care unit length of stay: recent changes and future challenges. Crit Care Med 2000;28(10): 3465–73.
[18] Rosenthal GE, Harper DL, Quinn LM, Cooper GS. Severity-adjusted mortality and length of stay in teaching and nonteaching hospitals. Results of a regional study. JAMA 1997;278(6):485–90.
[19] Niskanen M, Reinikainen M, Pettila V. Case-mix-adjusted length of stay and mortality in 23 Finnish ICUs. Intensive Care Med 2009;35(6):1060–7.
[20] Simchen E, Sprung CL, Galai N, Zitser-Gurevich Y, Bar-Lavi Y, Gurman G, et al. Survival of critically ill patients hospitalized in and out of intensive care units under paucity of intensive care unit beds. Crit Care Med 2004;32(8):1654–61.
[21] Mallor FA, C.; Barado, J. Control problems and management policies in health systems: application to intensive care units. Flex Serv Manuf J 2016;28(1):62–89.
[22] van de Klundert N, Holman R, Dongelmans DA, de Keizer NF. Data resource profile: the Dutch National Intensive Care Evaluation (NICE) registry of admissions to adult intensive care units. Int J Epidemiol 2015;44(6) (1850-h).
[23] Brown HP, R. Applied mixed models in medicine. United Kingdom: Wiley; 2015.
[24] Nakagawa S, Schielzeth H. A general and simple method for obtaining R2 from generalized linear mixed-effect models. Methods Ecol Evol 2013;4(2):133–42.
[25] Development Core Team R. A language and environment for statistical computing. 2.15.1 ed. Vienna, Austria: R Foundation for Statistical Computing; 2005.
[26] Bates D, Maechler M, Bolker B, Walker S, Christensen R, Singmann H, et al. Package lme4. 1.1-12 ed; 2016.
[27] Harell FE. Package rms. 5.1-0 ed; 2017.
[28] Peets AD, Boiteau PJ, Doig CJ. Effect of critical care medicine fellows on patient outcome in the intensive care unit. Acad Med 2006;81(10 Suppl):S1–4.
[29] Ruttimann UE, Pollack MM. Variability in duration of stay in pediatric intensive care units: a multiinstitutional study. J Pediatr 1996;128(1):35–44.
[30] Medeiros RS, NeSmith EG, Heath JA, Hawkins ML, Hawkins D, Bias R. Mid-level health providers' impact on ICU length of stay, patient satisfaction, mortality, and resource utilization. J Trauma Nurs 2011;18(3):149–53.
[31] Rothen HU, Stricker K, Einfalt J, Bauer P, Metnitz PG, Moreno RP, et al. Variability in outcome and resource use in intensive care units. Intensive Care Med 2007;33(8): 1329–36.
[32] Williams T, Leslie G. Delayed discharges from an adult intensive care unit. Aust Health Rev 2004;28(1):87–96.
[33] Barado J, Guergue JM, Esparza L, Azcarate C, Mallor F, Ochoa S. A mathematical model for simulating daily bed occupancy in an intensive care unit. Crit Care Med 2012;40(4):1098–104.
[34] Prin M, Wunsch H. The role of stepdown beds in hospital care. Am J Respir Crit Care Med 2014;190(11):1210–6.
[35] Logani S, Green A, Gasperino J. Benefits of high-intensity intensive care unit physician staffing under the affordable care act. Crit Care Res Prac 2011;2011:7 (Article ID 170814).
[36] Pronovost PJ, Angus DC, Dorman T, Robinson KA, Dremsizov TT, Young TL. Physician staffing patterns and clinical outcomes in critically ill patients: a systematic review. JAMA 2002;288(17):2151–62.
[37] Hackner D, Shufelt CL, Balfe DD, Lewis MI, Elsayegh A, Braunstein GD, et al. Do faculty intensivists have better outcomes when caring for patients directly in a closed ICU versus consulting in an open ICU? Hosp Pract (1995) 2009;37(1):40–50.
[38] Multz AS, Chalfin DB, Samson IM, Dantzker DR, Fein AM, Steinberg HN, et al. A “closed” medical intensive care unit (MICU) improves resource utilization when compared with an “open” MICU. Am J Respir Crit Care Med 1998;157(5 Pt 1): 1468–73.
[39] Pronovost P, Berenholtz S, Dorman T, Lipsett PA, Simmonds T, Haraden C. Improving communication in the ICU using daily goals. J Crit Care 2003;18(2):71–5.