The Utility of ICU Readmission as a Quality Indicator and the Effect of Selection*

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Objectives: Intensive care readmission rates are used to signal quality, yet it is unclear whether they represent poor quality in the transition of care from the ICU to the ward, patient factors, or differences in survival of the initial admission. This study aims to measure the selection effect of surviving the initial ICU admission on readmission rates.

Design: Retrospective cohort study of adult patients admitted to ICUs participating in the Case Mix Program database from the Intensive Care National Audit Research Centre.

Settings: The study includes 262 ICUs in the United Kingdom.

Patients: The study includes 682,975 patients admitted to ICUs between 2010 and 2014.

Interventions: None.

Measurements and Main Results: The study includes 682,975 patients admitted to ICUs in the United Kingdom. There were 591,710 patients discharged alive, of which 9,093 (1.53%) were readmitted within the first 2 days of ICU discharge. Post-ICU admission hospital mortality and ICU readmission were poorly correlated ($r = 0.130$). The addition of a selection model resulted in a weaker correlation ($r = 0.082$).

Conclusions: ICU readmission performed poorly as a performance metric. The selection process by which only patients who survive their index admission are eligible for readmission has a significant effect on ICU readmission rankings, particularly the higher ranked ICUs. Failure to consider this selection bias gives misleading signals about ICU performance and leads to faulty design of incentive schemes. (*Crit Care Med* 2018; 46:749–756)

Key Words: hospital mortality; intensive care unit readmissions; performance indicators; quality indicators; selection

***See also p. 821.**

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These data derive from the Intensive Care National Audit and Research Centre (ICNARC) Case Mix Programme Database. The Case Mix Programme is the national comparative audit of patient outcomes from adult critical care coordinated by ICNARC. For more information on the representativeness and quality of these data, please contact ICNARC.

The views and opinions expressed therein are those of the authors and do not necessarily reflect those of Intensive Care National Audit and Research Centre.

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THE EFFECT OF ICU MORTALITY ON READMISSION RATES

ICU readmissions have been associated with a protracted hospital stay, a higher cost, and increased mortality (1, 2). Several professional societies including the Society for Critical Care Medicine in the United States, the Australia and New Zealand Intensive Care Society, the U.K. Intensive Care Society, and the European Society of Intensive Care Medicine advocate using ICU readmission within 2 days of discharge as a quality indicator (3–5). This assumes that readmission represents preventable failures in the transition of care from the ICU to the ward, possibly from gap errors and other avoidable adverse events (6).

While this assumption may have strong face validity, there is a paucity of data to support this recommendation and there are conceptual concerns about using ICU readmission as a signal for performance (7). A good quality indicator should have not only strong face validity but also reproducibility, reliability, and feasibility (8). Additionally, it should have sufficient statistical variability to identify good and poor health providers, be relatively insensitive to the method of risk adjustment, and capture the quality of healthcare delivered, without inducing gaming (8). While intrinsic quality is difficult to directly observe, we might assume that, on average, higher quality ICUs have better health outcomes.

There is substantial variation in estimates of ICU readmission, ranging from 4.6% to 13.4% (1). This can be partly attributed to differences in patients' severity of illness or ICU case mix (9). There are also competing factors that may result in ICUs with high readmission rates but not necessarily in low quality (**eFig. 1**, Supplemental Digital Content 1, http://links.lww.com/CCM/D254). Readmission after unexpected clinical deterioration is an obvious risk factor for poor outcome in an individual patient but does not necessarily imply poor ICU performance.

Despite the large number of studies on ICU readmissions, there has been little regard for the selection effect of the index admission (10). Using the survivors of the index admission as the exposed cohort assumes that surviving the index admission is independent of the subsequent risk for readmission. However, ICU death during the index admission is an obvious competing risk for subsequent ICU readmission and the factors that drive mortality (e.g., illness severity) are similar to those that drive readmission. The probability of surviving the index admission is dependent on both measurable and non-observable patient characteristics. Risk adjustment models applied to survivors of the index admission can only account for measurable characteristics. Quality variation between ICUs is not perfectly observable because of incomplete risk adjustment. A good ICU is more likely to have a greater proportion of high-risk patients surviving their index ICU admission. These patients would have a higher probability of being readmitted, resulting in high-quality ICUs with an upwardly biased readmission rate because of incomplete risk adjustment.

At an ICU level, variables such as workload, ICU capacity, and average socioeconomic status have all been inconsistently associated with poorer quality discharge and may explain the observed variation in readmission rates (11–15).

This study examines the selection effect caused by surviving the index admission, by comparing only alive discharges versus all ICU admissions as the exposed cohort, on ICU readmission rankings.

MATERIALS AND METHODS

Data Source

Our study used a nationally representative sample of 262 U.K. critical care units from the Intensive Care National Audit and Research Centre (ICNARC) Case Mix Program (CMP) database to describe the epidemiology of ICU readmissions (16). The CMP is used for benchmarking and quality improvement. The use of this data has been approved for the CMP by the Confidentiality Advisory Group within the Health Research Authority—Approval Number: Patient Information Advisory Group 2–10(f)/2005. The institutional review board for Kings College Hospital waived the need for further consent.

Patients and Variables

Eligible patients were 16 years or older and admitted to the ICU between January 1, 2010, and December 31, 2014. Data were available on age, gender, ethnicity, socioeconomic group, comorbidities, dates for admission and readmission, length of ICU and hospital stay, indication for ICU admission, the use of mechanical ventilation and renal replacement therapy, decisions to limit treatment, clinical outcome, and discharge designation. There were also data on the type of ICU and the number of ICU beds. Only the first readmission during the index hospitalization was included. Subsequent ICU admissions after discharge home were excluded. All analyses were performed using Stata 14.0 (StataCorp, College Station, TX). The variables included in the models and details of patient flow are described in the **supplementary appendix** (**eTable 1**, Supplemental Digital Content 1, http://links.lww.com/CCM/D254; and **eFig. 2**, Supplemental Digital Content 1, http://links.lww.com/CCM/D254).

Readmissions were defined as any return to ICU within 2 calendar days after ICU discharge, during the index hospitalization. We assumed readmissions occurring within this time frame to be related to ICU care or transition failures and that readmissions occurring later may represent events unrelated to ICU (17). ICU length of stay was defined as the number of hours between admission and discharge. The proportion of patients with prolonged length of stay may reflect the ICU's average ability to treat and discharge low acuity patients efficiently (18). A prolonged length of stay was defined as a stay that exceeded the predicted length of stay by more than 24 hours. The predicted length of stay was calculated using illness severity, age, comorbidities, and mechanical ventilation. Mortality after ICU admission was adjusted using the ICNARC risk adjustment model which is developed specifically for U.K. ICUs and has been shown to have better discrimination than other models (19). Exposure variables to predict ICU readmission were based on prespecified findings from published literature (eTable 1, Supplemental Digital Content 1, http://links.lww.com/CCM/D254) (1, 10, 17, 20–23).

Statistical Analysis

A two-level variance component mixed-effects logistic regression approach was used to model ICU readmission rates. A multilevel model recognizes the clustered nature of the data and separates the total variance into separate components at the patient and ICU level.

We described differences between ICUs using the median odds ratio (MOR). The MOR translates these differences into a more intuitive odds ratio and can be conceptualized as the median value of the odds ratio between the ICUs at highest and lowest risk for readmission (24). The closer the MOR is to one, the more likely it is that there are no differences between ICUs.

We examined the effects of contextual variables on ICU readmission using the interval odds ratio (IOR) (24). An odds ratio is generated for each pair of patients with identical patient-level variables but who differ in a specific ICU-level variable and a distribution of these odds ratios is obtained (24, 25). The IOR is the interval around the median of the distribution that captures 80% of the distribution of the odds ratio values (25). The range of the IOR is wide if the between-ICU variability is large and narrow if the between-ICU variability is small. If the IOR does not contain 1, then the ICU-level covariate is considered significant in terms of inter-ICU variability (5). The details of the IOR and MOR computation are included in the supplementary appendix (Supplemental Digital Content 1, http://links.lww.com/CCM/D254).

We accounted for the effect of nonrandom selection by using a Heckman selection model. This method uses information from the selection process (in this case, the mortality from the index ICU admission) to correct the resulting bias.

There are three possible events that could occur to any patient admitted to the ICU: 1) surviving the index ICU admission and getting readmitted, 2) surviving ICU admission and not getting readmitted to the ICU, and 3) dying during the index ICU admission. The conventional approach assumes that surviving the index ICU admission is noninformative, that is, survival does not provide information about subsequent chances of readmission. If we assume that surviving the index ICU admission is uncorrelated with subsequent ICU readmission and that there are no competing factors, then we might expect a positive correlation with ICU mortality and ICU readmission, that is, poor-quality ICUs have high mortality and high readmission rates. If ICU readmission is a good performance indicator, this correlation should approach unity. If readmission is a poor indicator, it should approach zero.

We hypothesize that high-quality ICUs have a higher burden of high-risk patients surviving with the potential for readmission and that these survivors of the index admission differ in their risk of subsequent readmission in ways that are not observable. Selection models assume that the negative health characteristics related to mortality are incompletely observable and are correlated with the probability of ICU readmission. The best performing ICUs may be exposed to the largest burden of unobservably riskier patients for readmission. We may therefore see a weaker or even a negative correlation between mortality after ICU admission and ICU readmission rates when this selection effect is considered (**eFig. 3**, Supplemental Digital Content 1, http://links.lww.com/CCM/D254).

We ranked ICUs in terms of readmissions with the highest rank (first in the list) having the fewest readmissions. By examining the change in the ICU's ranking between the conventional approach and the inclusion of a selection model, we can evaluate the effect of ICU mortality on readmission rates. The change in an ICU's ranking can be described by plotting the two approaches on axes x and y and observing the deviation in the unit's ranking from the 45° line of unity. If the ICU ranking was not influenced by selection, then it would remain on the 45° line. If the ICU was above the 45° line, then it would imply that ICU has a higher ranking without the inclusion of the selection model. This suggests an ICU with a good ranking, which may have been achieved by greater mortality during the index admission. If an ICU was below the 45° line, that would imply the ICU performs better by including the effects of the selection model. This suggests a relatively good ICU with a higher burden of unobservably sicker patients, surviving to discharge with a greater risk for readmission. The further away from the 45° line, the more sensitive the ICU is to the selection effect.

RESULTS

Description of Patients and ICUs

A total of 682,975 patients were admitted to 262 ICUs between January 1, 2010, and December 31, 2014. There were 591,710 patients discharged alive during this period, of which 25,129 patients (4.25%) were readmitted during their index hospitalization with 9,093 (1.53%) readmitted within the first 2 days of ICU discharge (eFig. 2, Supplemental Digital Content 1, http://links.lww.com/CCM/D254). Compared with patients not readmitted, readmitted patients were older, more likely to reside in nursing home prior to admission and have higher illness acuity and more comorbidities (**Table 1**; and **eTable 2**, Supplemental Digital Content 1, http://links.lww.com/CCM/D254).

Patients receiving vasoactive drugs, mechanical ventilation, or renal replacement therapy during the index admission were more likely to be readmitted. An individual patient's socioeconomic class was not associated with readmission. Readmitted patients were more likely to have a prolonged length of stay during their index admission. This suggests that premature discharge was not a significant contributor to readmission and readmitted patients may be unobservably sicker.

Between 2010 and 2013, there was no significant change in ICU readmissions; however, in 2014, ICU readmissions were reduced by about 10% (**eTable 3**, Supplemental Digital Content 1, http://links.lww.com/CCM/D254). Specialist and larger ICUs were associated with lower readmission rates.

ICU-Level Variance

There was significant variation between ICUs in explaining an individual's risk for readmission. The MOR was 1.39 (95% CI, 1.34–1.45). A MOR greater than one suggests sufficiently important ICU-level variance in readmission rates. Another way of describing the MOR is to suggest that the same patient in a high-risk ICU was 1.39 times (in median) more likely to be readmitted than when in a low-risk ICU. The variation in risk-adjusted hospital mortality and ICU readmission is shown in **Figures 1** and **2**. The correlation between hospital mortality after ICU admission and ICU readmission was poor ($r = 0.130$) (**Fig. 3**).

Contextual Variables

The addition of ICU-level covariates (number of ICU beds, the mean socioeconomic status of the patients in the ICU, and the mean illness acuity of the patients in the ICU) had a minimal effect on the residual variance (**eTable 4**, Supplemental Digital Content 1, http://links.lww.com/CCM/D254). The wide IOR suggests substantial ICU-level heterogeneity, consistent with the previously described MOR. The IOR for each of these variables includes one and suggests that they do not significantly explain ICU-level variation in readmission rates.

Measuring the Effect of Sample Selection

ICU readmission was evaluated by assuming it was not independent of surviving the index admission using a two-step Heckman selection model (26). The coefficients for the model and the inclusion of a selection model are described in **eTable 5** (Supplemental Digital Content 1, http://links.lww.com/CCM/D254). The addition of a selection model results in a weaker correlation between ICU readmission and hospital

TABLE 1. Patient Characteristics at Discharge From Index ICU Admission

Variables	No Readmission, *n* (%)	Readmission Within 2 d, *n* (%)	*p*	OR	95% CI
n (%)	566,581 (98.42)	9,093 (1.58)			
Age quartiles					
< 50	148,463 (98.64)	2,045 (1.36)	–	1.0	–
50–64	141,772 (98.33)	2,411 (1.67)	< 0.001	1.23	1.16–1.31
65–75	133,053 (98.23)	2,398 (1.77)	< 0.001	1.31	1.22–1.37
> 75	143,293 (98.46)	2,239 (1.54)	< 0.001	1.13	1.06–120
Ethnicity					
White	512,710 (98.42)	8,206 (1.57)	–	1.0	–
Asian	18,675 (98.25)	333 (1.75)	0.055	1.11	0.99–1.24
Black	12,097 (98.46)	2,149 (1.74)	0.152	1.11	0.97–1.27
Mixed/other	23,099 (98.55)	339 (1.45)	0.133	0.92	0.82–1.02
Gender					
Female	251,215 (44.34)	3,656 (1.43)	–	1.0	
Male	315,366 (55.66)	5,437 (1.69)	< 0.001	1.18	1.14–1.23
Dependency					
Independent	449, 986 (98.46)	7,028 (1.54)	–	1.0	–
Minor assistance	91,087 (98.25)	1,626 (1.75)	< 0.001	1.15	1.08–1.21
Major assistance	21,003 (98.38)	346 (1.62)	0.337	1.05	0.94–1.17
Fully dependent	4,505 (98.06)	89 (1.94)	0.029	1.26	1.02–1.56
Acute Physiology and Chronic Health Evaluation II	14.26 (14.24–14.27)a	15.13 (15.00–15.24)a	< 0.001	1.02	1.02–1.03
Intensive Care National Audit and Research Centre	14.57 (14.55–14.59)a	15.87 (15.71–16.02)a	< 0.001	1.02	1.02–1.02
Type					
Medical	277,920 (98.58)	4,012 (1.42)	–	1.0	–
Surgical	288,648 (98.27)	5,081 (1.73)	< 0.001	1.22	1.17–1.27
Inotropes					
No	468,487 (98.49)	7,174 (1.51)	–	1.0	–
Yes	98,087 (98.08)	1,916 (1.92)	< 0.001	1.28	1.21–1.34
Mean number of days inotropes	0.50a (0.49–0.51)	0.62a (0.59–0.66)	< 0.001	1.26	1.21–1.31
MV					
No	340,986 (60.2)	4,952 (54.6)	–	1.0	–
Yes	225,595 (39.8)	4,126 (45.4)	0.001	1.00	1.00–1.01
Mean number of days MV	2.15a (2.13–2.17)	2.38a (2.24–2.50)	< 0.001	1.03	1.02–1.04
RRT					
No	525,937 (92.8)	8,234 (90.7)	–	1.0	
Yes	40,664 (7.2)	844 (9.3)	< 0.001	1.33	1.24–1.43
Mean number of days RRT	0.38a (0.38–0.39)	0.52a (0.48–0.56)	< 0.001	1,02	1.02–1.03
Prolonged ICU length of stay					
No	434,111 (98.38)	7,150 (1.62)		1.0	
Yes	132,463 (98.55)	1,943 (1.45)	< 0.001	0.89	0.85–0.94

MV = mechanical ventilation, OR = odds ratio, RRT = renal replacement therapy.
Mean and 95% CI of mean. Dashes signify the reference group.

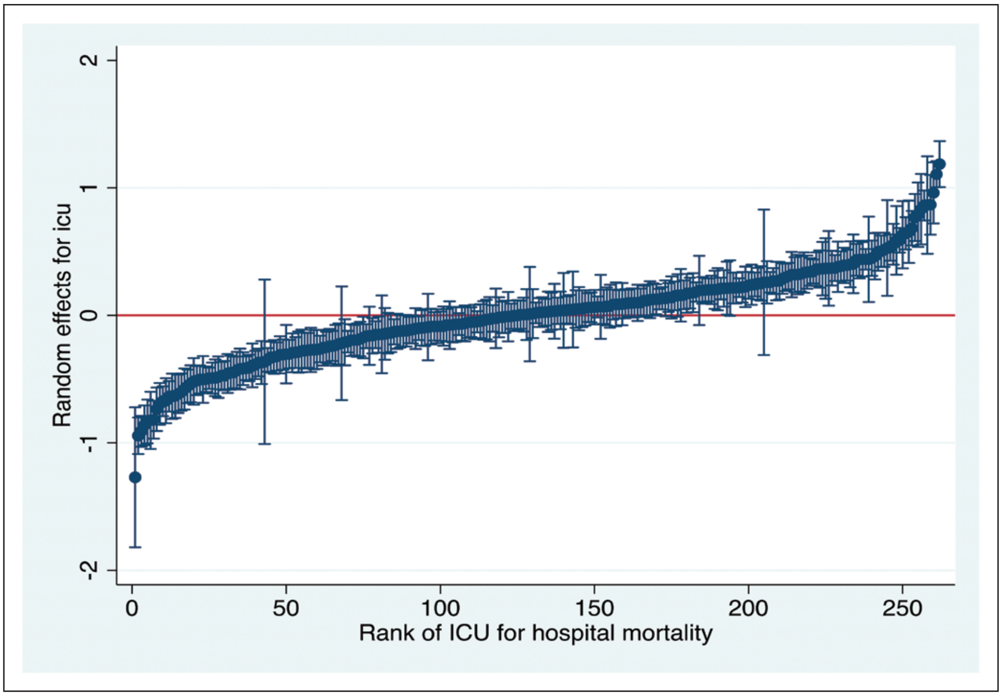

Figure 1. The rank of the ICU in terms of risk-adjusted mortality. The best performing ICU is ranked one and the worst performing ICU is ranked 262. The *y*-axis represents the latent variable for unexplained differences in mortality at the ICU level once measurable variables have been accounted for. These differences can be ascribed to differences in quality. A value of zero is the expected. A negative value in this context describes an ICU with a lower than expected mortality. A positive value describes an ICU with a higher than expected mortality.

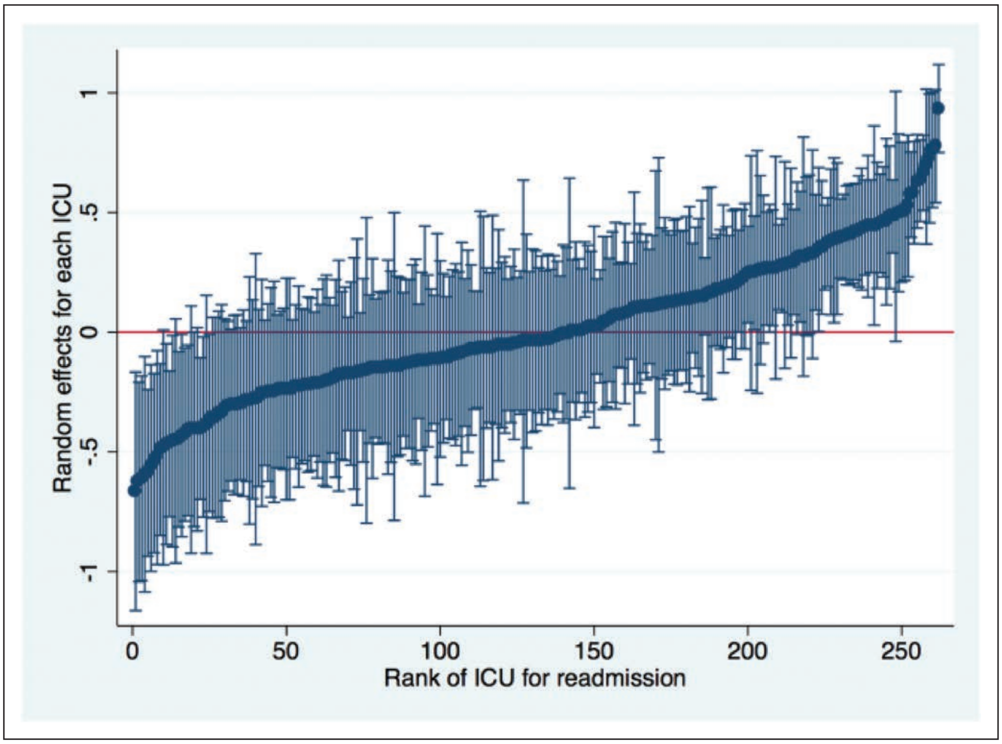

Figure 2. The rank of the ICU in terms of risk-adjusted readmissions. The best performing ICU is ranked one and the worst performing ICU is ranked 262. The *y*-axis represents the latent variable for unexplained differences in ICU readmission. Differences in the random effects variable can be ascribed to differences in quality. An ICU would expect to have a value of zero if the number of readmissions are within what is predicted based on measurable variables. A negative value in this context describes an ICU with a lower than expected rate of readmissions. A positive value describes an ICU with a higher than expected readmissions.

mortality ($r = 0.082$) (**eFig. 4**, Supplemental Digital Content 1, http://links.lww.com/CCM/D254). This suggests that sample selection effectively results in relative underestimations of the readmission rates in ICUs with higher mortality rates.

A graphical depiction of ICUs ranked by the conventional multilevel logistic model compared with the inclusion of a sample selection model to the multilevel model is shown in **Figure 4**. An ICU on the 45° line would not have their ranking influenced by selection. ICUs below the 45° line are ranked higher (more favorably) by the selection model than the multilevel logit model. The higher ranked ICUs appear more sensitive to the effects of the selection model.

Sensitivity Analysis

A sensitivity analysis was undertaken assuming all patients who died within 2 days of ICU discharge without a decision to withdraw life-sustaining therapy could be included as readmissions. This did not meaningfully alter the results and is included in **eTable 6** (Supplemental Digital Content 1, http://links.lww.com/CCM/D254).

DISCUSSION

This nationwide study shows that approximately 1.6% of patients are readmitted to the ICU within 2 days of discharge. Patients at risk for readmission were older, with more comorbidities and higher illness acuity and more likely to require vasopressors, mechanical ventilation, or renal replacement therapy.

There was sufficient evidence of differences between ICUs in terms of performance

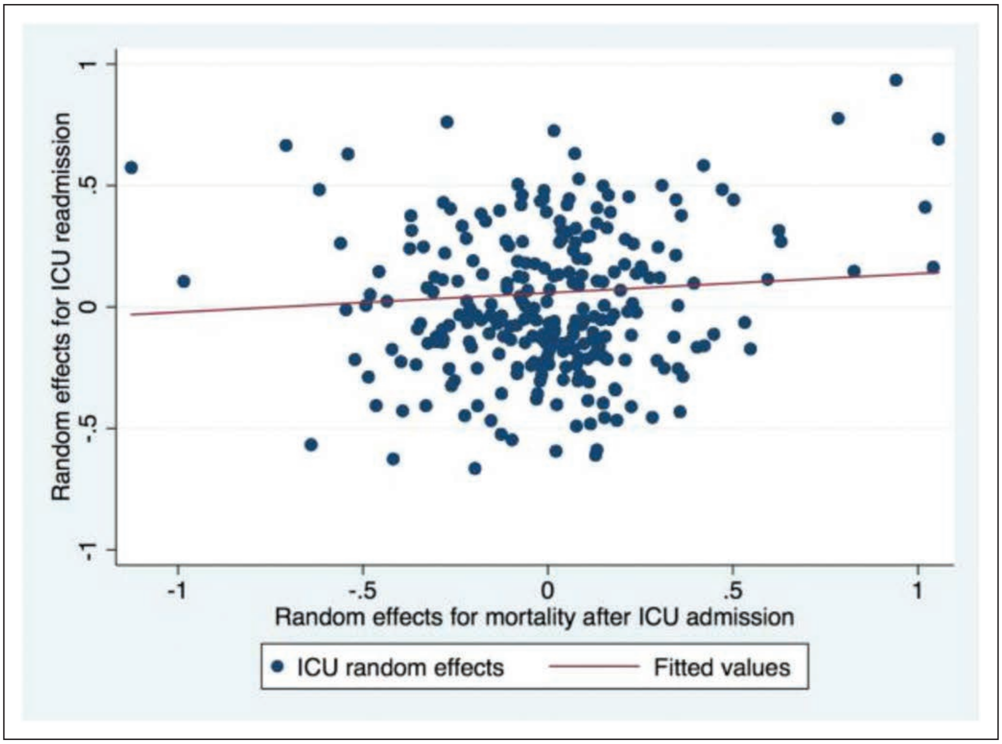

Figure 3. The correlation between hospital mortality after ICU admission and readmission. If intrinsic quality drives hospital mortality after ICU admission and ICU readmission, then the correlation would approach one. If the processes that drive hospital mortality after ICU admission and readmission are unrelated, then the correlation would approach zero.

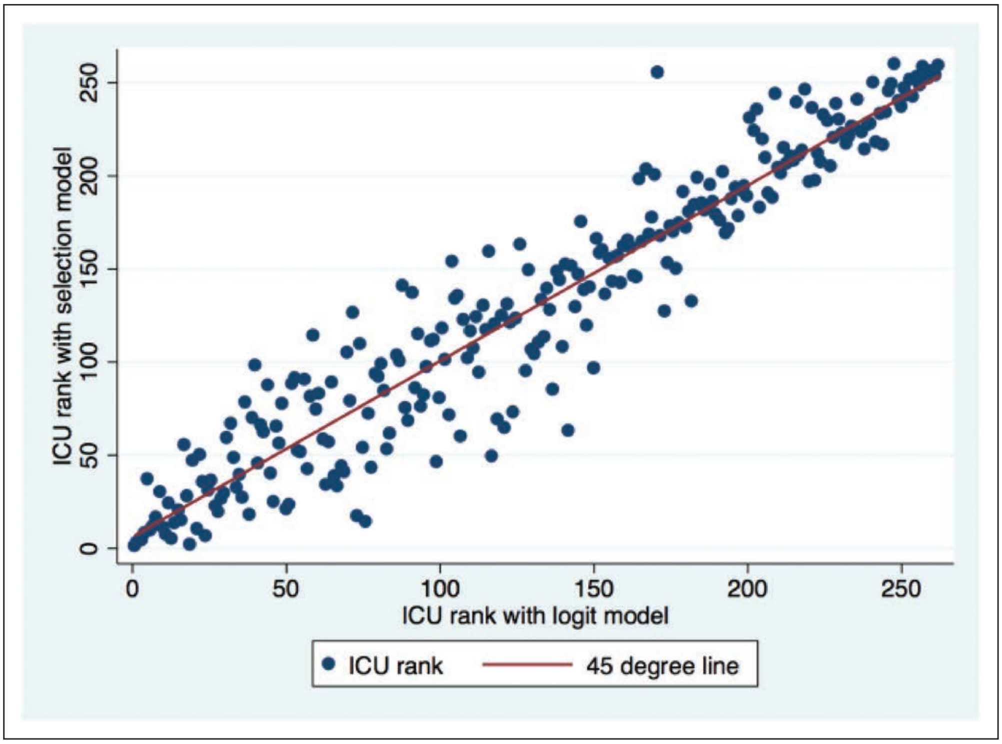

Figure 4. A comparison of ICU rank with and without accounting for the effects of selection. If death during the index admission had no effect of ICU readmission rates, then ICU would line up on the 45° line. ICUs below the 45° line had a better ranking when the selection model was included. This describes an ICU with an on-observably higher burden of high-risk patients for readmission. An ICU above the 45° line performs worse when selection is included. This describes an ICU where many high-risk patients die during the index admission reducing the risk for subsequent readmission.

in explaining an individual's risk for readmission. ICU-level variables (average illness severity, average socioeconomic status, and ICU size) did not significantly explain the observed variation.

If ICU readmission was a good quality indicator then, after adjusting for observable patient characteristics, there should be a strong positive correlation between mortality and readmission (eFig. 1, Supplemental Digital Content 1, http://links.lww.com/CCM/D254). Our study found a weak correlation between post-ICU admission hospital mortality and ICU readmission. This highlights the distinction between ICU performance and the implications of readmission for an individual's risk of mortality and is consistent with other studies of ICU readmission (1, 9, 27, 28).

Most studies on this topic assume that the process of patients surviving the index admission and any subsequent ICU readmission are independent of each other. We examined the effect of not assuming independence between these two events and show evidence of a correlation between surviving the index admission and subsequent readmission as manifested in changes to ICU rankings (29). The selection bias created by ignoring this correlation arises because of the unobservable patient characteristics that place patients at risk of a death and readmission (29). Conventional risk adjustment approaches are inadequate because some patient characteristics are only partially observable. The inclusion of a selection model altered the ICU ranking, that is, good ICUs with lower mortality had a higher number of high-risk patients likely to be readmitted. Some better performing (higher ranking) ICUs in terms of readmissions might have achieved this by having a larger share of unobservably sicker patients who do not survive the index admission.

ICU readmission rates are publicly reported and used to benchmark ICU performance. Ignoring the effect of sample selection may provide misleading signals about ICU performance and may generate perverse incentives. Organizations may take actions that improve the benchmark numerically but are costly and offer no substantive improvement in patient care.

The major strength of this study is that it uses a multilevel selection model to disaggregate the patient level and contextual effects of covariates. This model recognizes the hierarchical structure of the data and calculates the residual components for each level of the hierarchy and provides superior estimates than conventional multivariate regression techniques multilevel models account for the correlation between observations from the same cluster.

The study is further strengthened by using the CMP Database, which includes 100% of adult general ICUs in the United Kingdom. This makes our study one of the largest nationally representative studies of ICU readmission (30). The Case Mix Program Database uses rigorous methodology to ensure that the data are accurate and complete (30). The study also used a validated risk adjustment model that is specifically calibrated to critically ill patients in the United Kingdom but further residual confounding cannot be excluded (19)

This study was conducted in ICUs exclusively within the United Kingdom and may not be generalizable to other countries with a different case mix or organizational structure.

CONCLUSIONS

ICU readmission performed poorly as a performance metric. The selection process by which only patients who survive their index admission are eligible for readmission had a significant effect on ICU rankings, particularly the higher ranked ICUs. Analytic approaches to appropriately capture ICU performance on readmissions should include a selection model to avoid misleading signals about quality.

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