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ORIGINAL

ICU staffing feature phenotypes and their relationship with patients' outcomes: an unsupervised machine learning analysis

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Abstract

Purpose: To study whether ICU staffing features are associated with improved hospital mortality, ICU length of stay (LOS) and duration of mechanical ventilation (MV) using cluster analysis directed by machine learning.

Methods: The following variables were included in the analysis: average bed to nurse, physiotherapist and physician ratios, presence of 24/7 board-certified intensivists and dedicated pharmacists in the ICU, and nurse and physiotherapist autonomy scores. Clusters were defined using the partition around medoids method. We assessed the association between clusters and hospital mortality using logistic regression and with ICU LOS and MV duration using competing risk regression.

Results: Analysis included data from 129,680 patients admitted to 93 ICUs (2014–2015). Three clusters were identified. The features distinguishing between the clusters were: the presence of board-certified intensivists in the ICU 24/7 (present in Cluster 3), dedicated pharmacists (present in Clusters 2 and 3) and the extent of nurse autonomy (which increased from Clusters 1 to 3). The patients in Cluster 3 exhibited the best outcomes, with lower adjusted hospital mortality [odds ratio 0.92 (95% confidence interval (CI), 0.87–0.98)], shorter ICU LOS [subhazard ratio (SHR) for patients surviving to ICU discharge 1.24 (95% CI 1.22–1.26)] and shorter durations of MV [SHR for undergoing extubation 1.61(95% CI 1.54–1.69)]. Cluster 1 had the worst outcomes.

Conclusion: Patients treated in ICUs combining 24/7 expert intensivist coverage, a dedicated pharmacist and nurses with greater autonomy had the best outcomes. All of these features represent achievable targets that should be considered by policy makers with an interest in promoting equal and optimal ICU care.

Keywords: Intensive care unit, Outcomes, Cluster analysis, Nurse autonomy, Staffing features, ICU organization

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Dieter E. S. Araya: In Memoriam.

Introduction

Understanding how organization and processes of care affect intensive care unit (ICU) performance is paramount to providing recommendations for critical care practitioners and administrators. Over the last years, several studies have provided data that have guided formation of models of care associated with better patient outcomes and more efficient ICU resource use [1–4]. Previous studies have focused mostly on staffing density [2–5] and qualification [6, 7], the use of protocols [1, 8], daily checklists [9] and multidisciplinary rounds [10]. Few reports have studied the relation between staff autonomy (especially, non-physician ICU staff), patient outcomes and ICU performance [11–15]. Additionally, organizational and staffing features have a complex interplay. They should therefore ideally be considered together rather than independently. For instance, regardless of the number of staff members, patient outcomes and ICU performance may vary according to staff qualifications and autonomy. We applied clustering analysis to identify "ICU phenotypes" according to staffing features and the degree of clinician autonomy and to investigate the relationship between "phenotype", patient outcomes and ICU performance.

Take–home message

Machine learning reinforces prior observations that patient's outcomes and ICU performance are better when several staffing features are combined, namely: 24/7 presence of a board-certified intensivist, a dedicated ICU pharmacist and high levels of nurse autonomy.

Methods

Design and setting

This retrospective analysis was performed on data prospectively collected from consecutive adult patients (≥ 16 years old) admitted to 93 medical–surgical ICUs at 55 Brazilian hospitals during 2014 and 2015. A detailed description of the methods, including patient inclusion and exclusion criteria, is presented in the Electronic Supplementary Material (ESM, Appendix 1). The patient inclusion/exclusion process is depicted in Fig. 1. The complete list of the investigators and study centers may be found in ESM Appendix 2. Local Ethics Committees and the Brazilian National Ethics Committee (CAAE: 19687113.8.1001.5249) approved the study without the need for informed consent.

We retrieved de-identified patient data from the Epimed Monitor System® (Epimed Solutions®, Rio de Janeiro, Brazil) [16]. Patient data were routinely collected by trained medical personnel (usually nurses). These included demographics, admission diagnosis, comorbidities based on the Charlson Comorbidity Index (CCI), performance status (PS) in the week before hospital admission [17], Simplified Acute Physiological Score 3 (SAPS 3 [18]), Sequential Organ Failure Assessment (SOFA) score [19] at admission, use of organ support and ICU and hospital outcomes.

All medical–surgical ICUs registered in the Brazilian Research in Intensive Care Network (BRICNet) database that routinely use the Epimed Monitor System® were invited to participate in the study. Specialized ICUs (e.g., cardiac, coronary care) were excluded. Parallel to data analysis, we performed a cross-sectional structured survey of hospital and ICU organizational, structural and process characteristics. To this end, interviews were conducted with the ICU director and/or the chief nurse from every participating center on site or by phone. The data surveyed included ICU and hospital bed capacity, ICU staffing patterns, the presence of training programs in critical care, multidisciplinary rounds, checklists, handover procedures and a set of six pre-specified clinical protocols aimed at preventing ICU-acquired complications (ESM, Appendix 3). We also assessed non-physician staff members' autonomy by surveying the chief nurse and lead physiotherapist. For this purpose, we developed two simple questionnaires investigating the degree of nurse and physiotherapy staff independence in performing seven pre-specified tasks related to patient care (ESM, Appendix 4). For each task, possible answers were "no" (never allowed, arbitrarily assigned 0 points), "sometimes" (allowed for some patients or eventually, 1 point) or "yes" (always allowed, except in very specific situations, 2 points). The final autonomy score for nurses and physiotherapists was calculated as the sum of these tasks (ranging between 0 and 14 points).

Outcomes

The primary outcome of interest was in-hospital mortality, which was also assessed as aggregate data and trends over time. Secondary outcomes were lengths of ICU stay (LOS) and durations of mechanical ventilation (MV) in ventilated patients.

Statistical analysis

Clustering algorithm: We selected the following variables related to ICU staffing patterns, qualification and autonomy for clustering: average bed/nurse, bed/physiotherapist and bed/physician ratios, presence of a board-certified intensivist in the ICU 24/7 (in-house), presence of ICU dedicated pharmacist and total nurse and physiotherapist autonomy scores to create clusters based on the 93 participating ICUs. We used partitioning

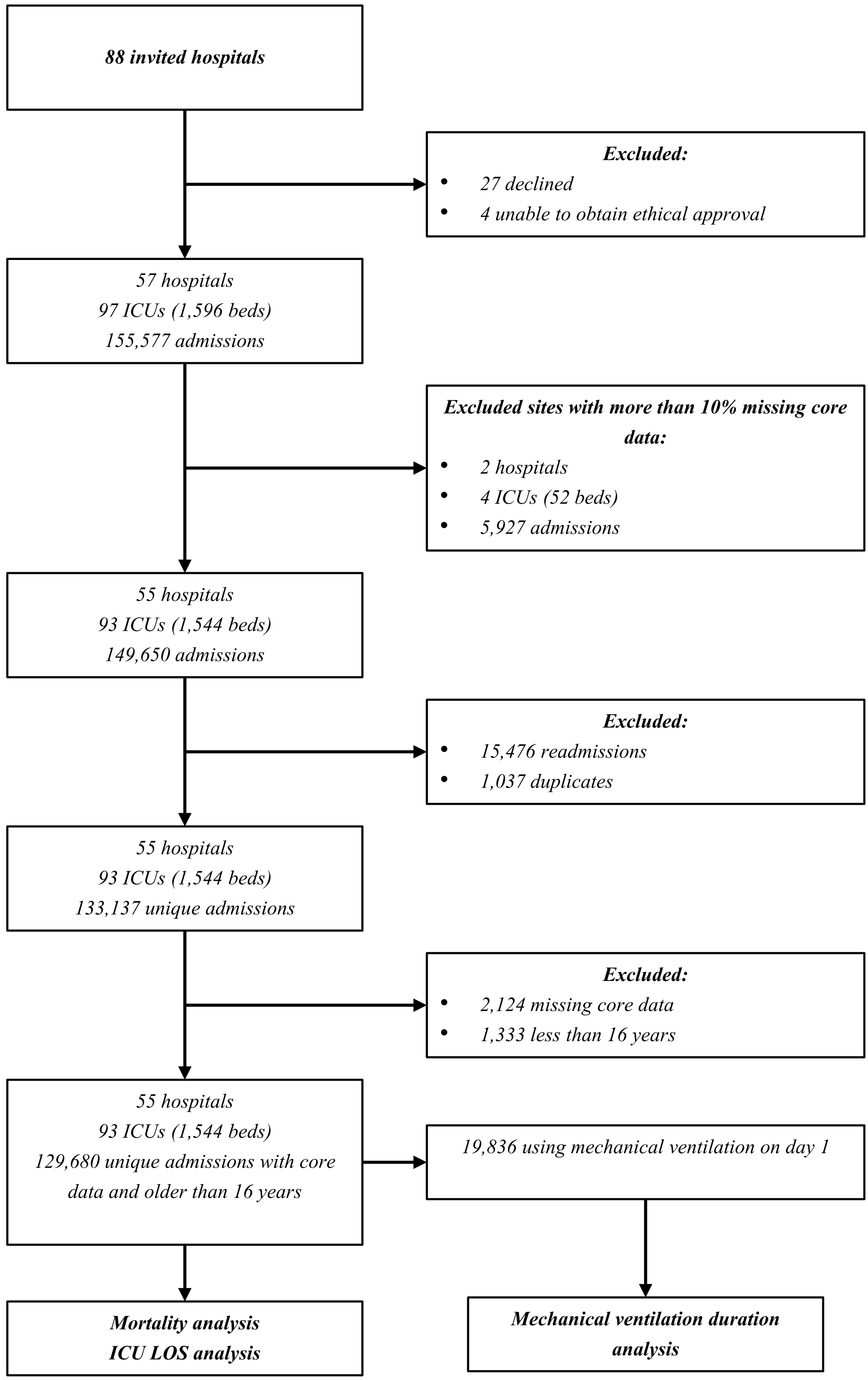

Fig. 1 Study flowchart

around medoids to cluster data, defining the ideal number of clusters according to predefined criteria (ESM, Appendix 1) [20]. After clustering, we assessed whether the organizational characteristics were distinguishable among the clusters. We applied sensitivity analyses to assess cluster robustness and to examine the stability of the clustering process.

Patient outcomes: Logistic regression was used to examine if hospital mortality differed among the clusters. Models included the independent variable of cluster with adjustment for age, hospital LOS before ICU admission, admission type (medical, elective surgery and urgent surgery), use of MV at admission, CCI, PS, SOFA score, the admission cluster and the interaction between SOFA and cluster (ESM, Appendix 1). The interaction was added to account for differences in ICU´s performance that could vary according to the acuity of the admitted patient (in other words, the association between SOFA and outcome may change according to the cluster the patient was admitted). These variables were elected based on clinical logic due to a high likelihood of differences in baseline patient characteristics between clusters. Results were displayed as the predicted mortality according to varying SOFA scores in each cluster. We performed subgroup analyses for mortality stratifying patients according to the admission type (unplanned vs. elective surgical). We also assessed ICU performance over time by plotting the variable-adjusted life display (VLAD) of each cluster throughout the study period; every time a patient survived, their probability of death according to the SAPS 3 score was added, and vice versa. The end result reflects the overall cumulative survival over time. To ensure that the correct tool was selected for the VLAD, we used visual trend analysis display of monthly hospital mortality and the mean predicted cluster mortality by the SAPS 3 score and also measured the calibration and discrimination capability of SAPS 3 over time.

Sensitivity analyses were performed for (1) the predicted probability of inclusion in Cluster 1 set as reference to examine the effect of the clustering method used and (2) the potential bias in admission policies within each cluster (using a multinomial propensity score for the probability of ICU admission between each cluster). To calculate the proportion of deaths attributable to admission to a cluster with worse performance, an attributable fraction analysis was performed.

Finally, for ICU LOS and MV duration, we applied a competing risk model since mortality at any point competes with both ICU LOS and MV duration [21]. Both analyses were adjusted for the same variables as in the main logistic regression model for mortality and were censored at 28 days. For MV duration, we only included patients undergoing MV within the first day after ICU admission. Data are presented as subhazard ratios (SHRs).

We applied median imputation for the very few variables with missing data < 1% (ESM, Appendix 1). The pre-specified conceptualization of the analysis plan is described in the Appendix 5 of ESM. We followed the STROBE report for this manuscript (ESM, Appendix 6) [22]. We performed all analyses in R (version 3.6.0).

Results

Characterization of ICUs and patients among clusters

A total of 129,680 patients admitted to 93 participating ICUs were analyzed (study flowchart, Fig. 1). The mean number of beds per nurses, physiotherapists and physicians was 5.15 (SD 2.50), 10 (SD 2.67) and 7.19 (SD 1.93), respectively. The mean nurse autonomy score was 6.32 (SD 3.49) and the mean physiotherapist autonomy score was 9.77 (SD 3.45). A board-certified intensivist was available 24/7 in 16 (17.2%) of the ICUs. A dedicated pharmacist was available in 50 (53.8%) of the ICUs.

Cluster analysis suggested three clusters (sFigures 1, 2 and 3). The clusters identified were well separated and differed most significantly in three characteristics: the presence of a board-certified intensivist in the ICU 24/7, the presence of a dedicated pharmacist and nurse autonomy score. Table 1 presents the main differences in cluster characteristics. sTable 1 presents additional differences between the clusters. Nurse autonomy in titrating vasopressors, sedation and nutrition, and in starting weaning from MV and active mobilization increased from Cluster 1 to Cluster 3 (Fig. 2 and sTable 1). Differences in physiotherapist autonomy score domains were observed only in starting weaning (higher autonomy in Cluster 3) and passive mobilization (higher autonomy in Clusters 2 and 3); results are shown in sFigure 4 and sTable 1. Sensitivity analyses confirmed clustering robustness and stability (ESM, page 23; sFigure 5).

The main characteristics of the patients admitted to each cluster are presented in Table 2. Patients in Cluster 3 had higher SOFA scores and required more ICU organ support (specifically vasopressors and renal replacement therapy). Unadjusted ICU and hospital mortality rates were lowest in Cluster 2. Cluster 2 also had the lowest illness severity (SAPS 3 and SOFA scores and organ support).

Outcome analysis

Patients admitted to the ICUs in Cluster 3 displayed the lowest adjusted hospital mortality (Fig. 3a). The odds ratio (OR) for mortality among patients admitted to Cluster 2 versus Cluster 1 was 0.92 [95% confidence interval (CI) 0.87–0.98] and for Cluster 3 versus Cluster 1 was 0.69 (95% CI 0.64–0.75). This association remained

Table 1 Comparison of ICU organizational characteristics among clusters ($n = 93$)

	Cluster 1 $n = 40$ (43.0%)	Cluster 2 $n = 37$ (39.8%)	Cluster 3 $n = 16$ (17.2%)	*P* value
Number of ICU beds, mean (SD)	13.8 (6.79)	18.0 (12.4)	21.1 (10.9)	0.03
Main source of funding, *n* (%)				0.01
Public	15 (37.5)	4 (10.8)	2 (12.5)	
Private	25 (62.5)	32 (89.2)	14 (87.5)	
Beds/nurse, mean (SD)*	6.01 (2.52)	6.03 (1.85)	6.75 (3.63)	0.58
Beds/physiotherapist, mean (SD)*	9.89 (2.55)	10.4 (2.88)	9.41 (2.44)	0.41
Beds/physician, mean (SD)*	6.91 (1.95)	7.57 (2.03)	7.01 (1.59)	0.31
Nurse autonomy score (points), mean (SD)*	4.17 (2.56)	7.22 (3.07)	9.62 (3.03)	< 0.01
Physiotherapist autonomy score (points), mean (SD)*	8.72 (3.56)	10.4 (3.38)	10.9 (2.69)	0.03
Dedicated pharmacist, *n* (%)*				< 0.01
No	40 (100%)	0 (0.00%)	3 (18.8%)	
Yes	0 (0.00%)	37 (100%)	13 (81.2%)	
Board-certified intensivist 24/7 in the ICU, *n* (%)*				< 0.01
No	40 (100%)	37 (100%)	0 (0.00%)	
Yes	0 (0.00%)	0 (0.00%)	16 (100%)	
Number of protocols, mean (SD)**	4.97 (1.46)	5.70 (0.62)	5.75 (0.58)	< 0.01
Training program in critical care, *n* (%)	19 (47.5)	19 (51.3)	9 (56.2)	0.83
ICU multidisciplinary rounds, *n* (%)				0.25
No rounds	3 (7.50%)	0 (0.00%)	1 (6.25%)	
Some days a week	3 (7.50%)	3 (8.11%)	2 (12.5%)	
During weekdays	13 (32.5%)	15 (40.5%)	9 (56.2%)	
During weekdays and weekends	21 (52.5%)	19 (51.4%)	4 (25.0%)	

ICU intensive care unit, *SD* standard deviation

*Variables used for clustering algorithm

**Out of a total of six clinical protocols aimed at to prevent ICU-acquired complications

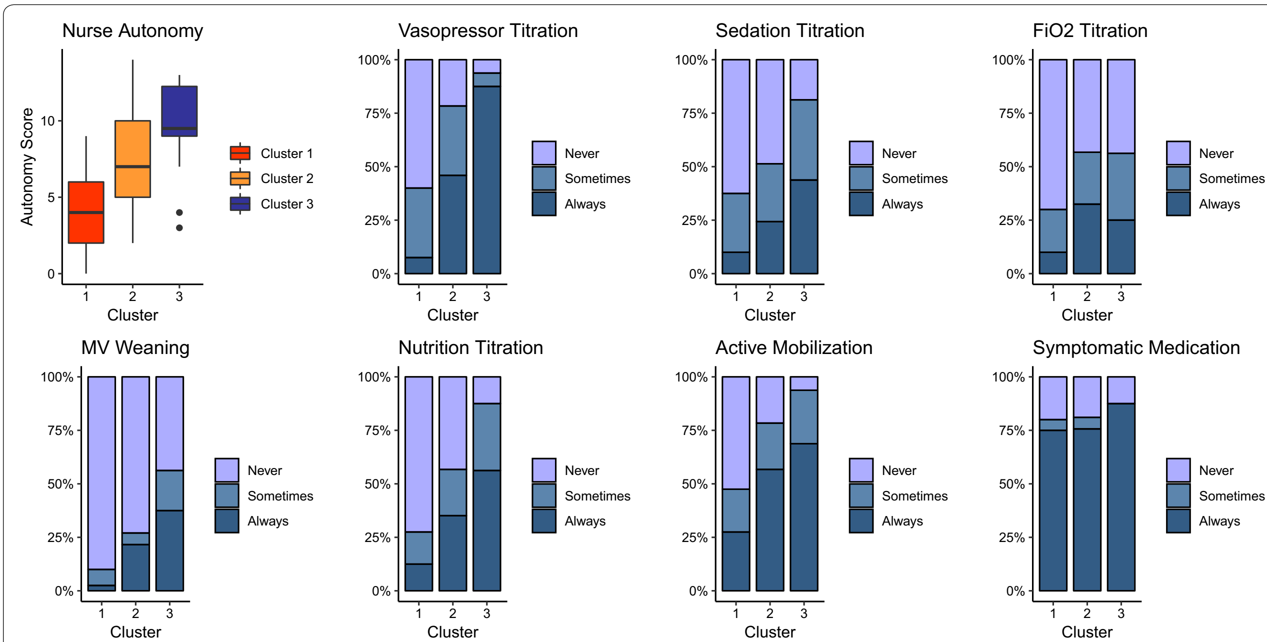

Fig. 2 Top left: nurse autonomy score according to cluster. Each following panel represents the autonomy level of nurses in each ICU cluster regarding each autonomy component of nurse autonomy score

Table 2 Comparison of patients admitted to each cluster ($n = 129,680$)

	Cluster 1 $n = 48,329$ (37.2%)	Cluster 2 $n = 52,282$ (40.3%)	Cluster 3 $n = 29,069$ (22.4%)	*P* value
Age (years), mean (SD)	60.9 (20.1)	62.3 (19.8)	63.5 (18.6)	< 0.01
SAPS 3 (points), mean (SD)	47.5 (17.4)	43.5 (14.3)	44.9 (16.7)	< 0.01
SOFA (points), mean (SD)	3.55 (4.12)	2.59 (3.01)	3.73 (3.63)	< 0.01
Admission type, *n* (%)				< 0.01
Elective surgery	9142 (18.9%)	12,748 (24.4%)	10,488 (36.1%)	
Medical	33,667 (69.7%)	37,651 (72.0%)	16,716 (57.5%)	
Urgent surgery	5520 (11.4%)	1883 (3.60%)	1865 (6.42%)	
CCI (points), mean (SD)	1.40 (1.86)	1.37 (1.83)	1.78 (1.99)	< 0.01
Vasopressor use, *n* (%)				
At admission	5909 (12.2%)	4529 (8.66%)	4060 (14.0%)	< 0.01
During ICU stay	6879 (14.2%)	7964 (15.2%)	6624 (22.8%)	< 0.01
MV, *n* (%)				
At admission	9313 (19.3%)	5716 (10.9%)	4807 (16.5%)	< 0.01
During ICU stay	12,250 (25.3%)	9583 (18.3%)	6975 (24.0%)	< 0.01
MV duration, days, median [IQR]	5 [1–11]	2 [0–9]	2 [1–7]	< 0.01
Noninvasive ventilation, *n* (%)				
At admission	3723 (7.70%)	2500 (4.78%)	2088 (7.18%)	< 0.01
During ICU stay	6218 (12.9%)	4754 (9.09%)	4089 (14.1%)	< 0.01
Renal replacement therapy, *n* (%)				
At admission	1233 (2.55%)	457 (0.87%)	295 (1.01%)	< 0.01
During ICU stay	3043 (6.30%)	2747 (5.25%)	2339 (8.05%)	< 0.01
ICU LOS (days), mean (SD)	3 [1–6]	3 [1–6]	2 [1–5]	< 0.01
Hospital LOS (days), mean (SD)	9 [4–19]	8 [4–16]	10 [5–21]	< 0.01
Discharge status, *n* (%)				< 0.01
Home	34,873 (72.2%)	42,754 (81.8%)	23,421 (80.6%)	
Home-care with need of nursing care/ Hospice	2284 (4.73%)	1762 (3.37%)	1023 (3.52%)	
Dead	11,172 (23.1%)	7766 (14.9%)	4625 (15.9%)	

SAPS simplified acute physiology score, *SOFA* Sequential Organ Failure Assessment, *CCI* Charlson Comorbidity Index *ICU* intensive care unit, *SD* standard deviation; *LOS* length of stay

consistent in subgroup analysis for unplanned (Fig. 3b) and planned surgical (Fig. 3c) admissions. VLAD analysis of cumulative excess survival adjusted for the number of ICU admissions followed the same pattern, with progressively positive values for Cluster 2 and even more so for Cluster 3 and with negative cumulative values for Cluster 1 (Fig. 3d). Temporal analysis showed that ICUs in Cluster 3 had hospital mortality rates consistently lower than the SAPS 3 predicted mortality during the study period; the opposite was observed for those in Cluster 1. ICUs in Cluster 2 had again intermediate performance. SAPS 3 accuracy and calibration were stable during the study period (sFigure 6 and 7).

Sensitivity analysis for the effect of the clustering method used also showed an increased probability of death among patients admitted to Cluster 1 (sFigure 8). Adjustment for the potential bias in admission policies resulted in a good balance between clusters after propensity scoring (sFigures 9 and 10). Sensitivity analysis after this adjustment also showed that the OR for hospital death was lower in patients admitted to Clusters 3 (0.94; 95% CI 0.94–0.95, $P < 0.01$) and 2 (0.98; 95% CI 0.97–0.98, $P < 0.01$). Overall, 17.8% of the deaths in Clusters 1 and 2 could theoretically be attributed to admission to a cluster other than Cluster 3.

Analysis of ICU LOS after controlling for mortality showed longer ICU LOSs in Cluster 2 than in Cluster 1 (SHR 0.98; 95% CI 0.97–0.99, $P < 0.01$) and shorter ICU LOSs in Cluster 3 than in Cluster 2 (SHR 1.24; 95% CI 1.22–1.26, $P < 0.01$). Patients in Cluster 1 also were also at greater hazard of prolonged MV compared to those in Clusters 2 and 3 (SHR 1.49; 95% CI 1.43–1.56, $P < 0.01$ when compared to Cluster 2; and SHR 1.61; 95% CI 1.54–1.69, $P < 0.01$ when compared to Cluster 3).

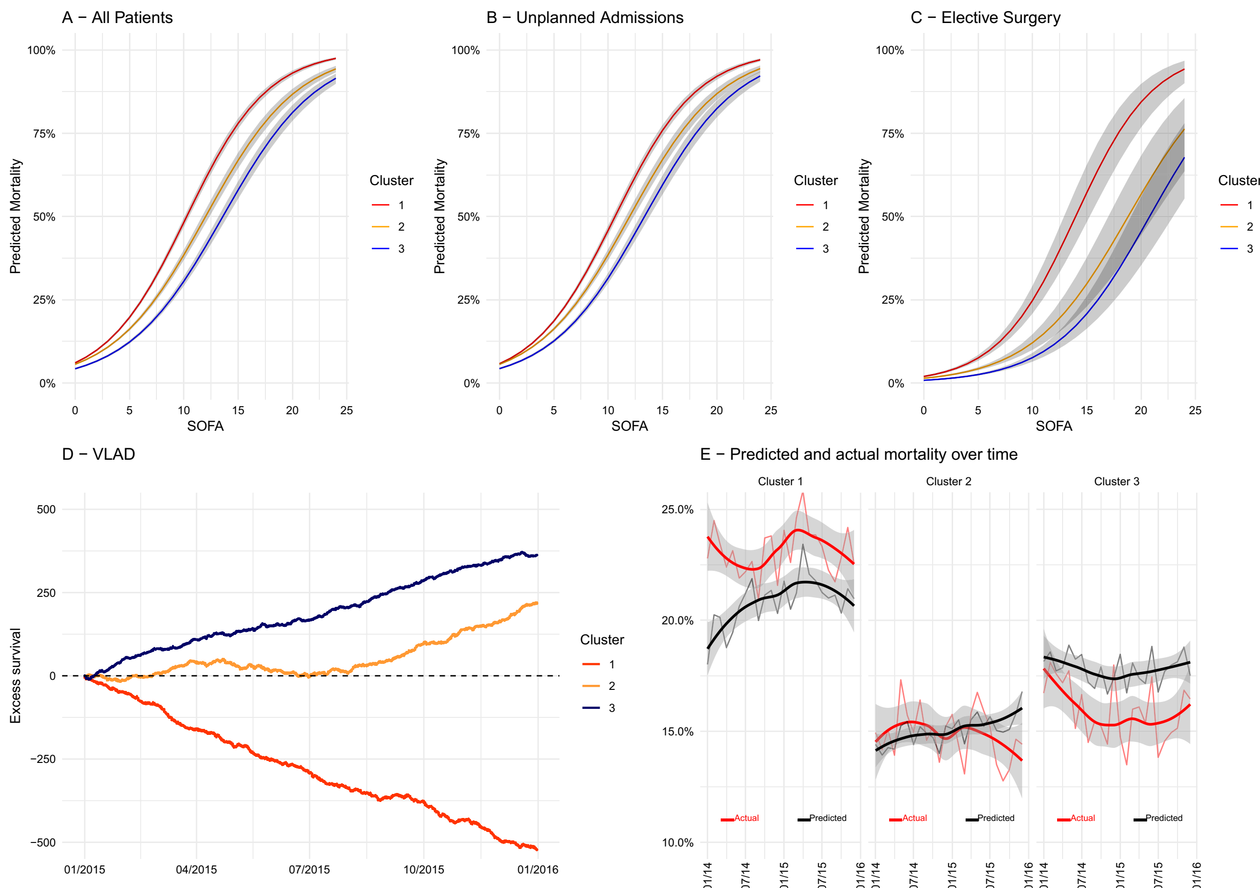

Fig. 3 **a** Counterfactual predicted mortality according to SOFA score in each cluster for all patients. **b** Predicted mortality according to SOFA score in each cluster for unplanned admissions. **c** Predicted mortality according to SOFA score in each cluster for planned surgical admissions. **d** Cumulative excess survival in each cluster during time. **e** SAPS 3 predicted (thin black line) versus actual (thin red line) for mortality at each month in each cluster. The bold lines represent a smoother version of the thin lines. For **a**–**c**, values of SOFA in the model were varied while keeping other predictors constant. The plots consider predictions for age = 64 years, medical admission, no mechanical ventilation on admission, CCI = 1, absence or minor previous performance status impairment and length of stay before ICU admission of 0 days

Discussion

We used a machine learning algorithm for profiling ICU phenotypes according to multiple staffing features in a large cohort and identified three distinct ICU clusters differing in three major features: the presence/absence of board-certified intensivists 24/7, a dedicated ICU pharmacists and nurse autonomy. Our analysis identified these staffing features that, when implemented together, may benefit many patients admitted to the ICU in terms of survival.

Patients admitted to the ICUs in Cluster 3 had the lowest mortality rates and shorter ICU LOS. This cluster was characterized by the presence of board-certified intensivists 24/7 in all ICUs, a dedicated pharmacist in most of them and markedly higher nurse autonomy. Patients admitted to Cluster 1 had the worst survival outcomes. In this cluster, coverage by ICU care providers was poorest and nurses had the lowest autonomy scores. MV durations were comparable in Clusters 2 and 3, but both of these were more prolonged than in Cluster 1. Our findings remained robust in sensitivity analyses testing different clustering techniques and potential differences in admission policies. Cumulative performance improved over time in Clusters 2 and 3, but worsened in Cluster 1. Small ORs, such as those found in our study, can have a huge impact when the intervention is used in a very large number of patients.

The most important contribution of this manuscript is the multidimensional approach, which enabled investigation into associations far broader than just the association between the number or the training of staff members with the outcomes. Cluster analysis enabled us to assess the effect of ICU profiles instead of individual effects of specific staffing patterns. In this our study is unique. Previous studies have investigated the association between individual staffing features and outcomes, thereby failing to capture the potential interplay among them that might explain the different results [2–7, 10–15, 23]. Our approach describes how the interaction between staff numbers and the specifics of staffing features (e.g., composition, training, autonomy) may affect outcomes. This model is much more relevant to a setting where collaborative multiprofessional teamwork occurs. Merely adding or changing a staffing pattern may not result in improved care. However, identifying specific staffing feature profiles associated with improved outcomes and performance may serve to tailor staffing features in future initiatives.

Our results reinforce that ICUs should be run by board-certified intensivists [2]. Consistent with our results, previous reports also demonstrated that the presence of dedicated pharmacists in the ICU is associated with better outcomes [2]. We found that the higher the nurse autonomy to take actions, the better the patients' outcomes and ICU performance. Previous studies demonstrated that nurse-led interventions can result in early initiation and timely escalation of enteral feeding [23], improved weaning and increased adherence to best practices in MV patients [11, 12, 24], sedation minimization and better assurance of patients' comfort [13]. In addition, increasing nurse autonomy is also associated with higher safety culture in the ICU, which ultimately can improve patients' care [25]. Conversely, lower levels of autonomy are associated with higher intention to leave the job [26], anticipated turnover [27] and moral distress [28, 29], and contributes adversely to nurse–physician collaboration [29].

This study has several strengths and novel findings. We were able to gather patients' data prospectively collected in many ICUs and organizational features were surveyed by direct interview with staff leaders. We also propose a simple way to measure nurse and physiotherapist autonomy. Direct assessment of nurse autonomy in critical care through staffing survey based on a simple questionnaire provided relevant information associated with improved patient-centered outcomes.

However, our study has also several constraints. Causal inference cannot be confirmed because each ICU may have different admission policies that could affect outcomes. In fact, all the differences between clusters regarding autonomy and staffing patterns may be a proxy for other hidden or unmeasured features not captured by the clustering method, such as staff burnout, job strain and workload, and team experience. Clusters may also differ in other structural and organizational characteristics that were not captured in the models but may also influence patient outcomes and ICU performance (e.g., teaching status). Staff autonomy was assessed by surveying the staff leaders. Their responses may not represent the real staff perceptions The autonomy scores, created specifically for this study, have not been validated. Staff autonomy may also have changed during the study period in specific units. We also lack details on the roles and levels of autonomy of pharmacists in the studied ICUs. All of these limitations should be addressed in future studies. Additionally, despite the relatively large number of ICUs included, there were limitations to performing subgroup analyses based on ICU-level characteristics (e.g., the level of ICU acuity, source of funding and hospital size). Finally, these results reflect the organizational features of a large sample of Brazilian ICUs and may not be generalizable to other settings. It is important to note that the bed to nurse and physiotherapist ratios in this dataset were substantially higher than those reported not only in high-income, but also in other low- and middle-income countries [3].

Conclusion

A machine learning approach using cluster analysis revealed the ICU staffing feature profiles that were associated with better ICU patient outcomes. After adjustment for patient and other characteristics, ICUs with 24/7 intensivist coverage, with a dedicated pharmacist and with higher nurse autonomy did best in terms of having the lowest mortality, shortest ICU LOSs and shortest duration of MV. These staffing features represent achievable targets that should be considered by policy makers with an interest in promoting equal and optimal ICU care.

Electronic supplementary material

The online version of this article (https://doi.org/10.1007/s00134-019-05790-z) contains supplementary material, which is available to authorized users.

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Compliance with ethical standards

Conflicts of interest

JIFS and MS are founders and proprietors of Epimed Solutions®. LPB is an employee of Epimed Solutions®. FGZ has received grant for an investigator-initiated clinical trial from Bactiguard®, Sweden, which is unrelated to the aspects of this work. The other authors report no conflicts of interest to declare.

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