

International Comparison of Critically Ill Patients

by Maria I. Fabre

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Submitted to the
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ABSTRACT

Severity of illness scores are useful in quality improvement for benchmarking care in the ICU and in research for risk-adjustment. ^[1] However, these scores lack generalizability beyond the patients on whom the scores were trained on. An international consortium, Global Open Source Severity of Illness Score (GOSSIS) Project, has put together various databases to create a definition of critical care severity independent of geographic and cultural data. ^[2] In order to combine the databases efficiently, 200 variables of interest were identified and extracted from the databases, when possible. Some variables showed different distributions throughout the databases that can be attributed to differences in medical practices and selection bias of hospitals. Thus, the predictive models that were trained in one database scored poorly when tested on a different database. Thus, a combination of the extracted variables from different databases with some necessary data manipulation should create a more generalizable severity of illness score.

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I am grateful to all my professors and classmates whom were part of my career at M.I.T. My experience at M.I.T. would not have been as magical without my friends, thank you for encouraging me to be happy and to be myself.

I will be eternally grateful to my family: my life-coach (mother), my childhood friend (father), my cheerleader (Chapiz), my mentor (Andrea), my comedian (Alejandra), and of course, my Angel (Leonardo).

Motivation

Severity of illness scores are useful in quality improvement for benchmarking care in the ICU and in research for risk-adjustment.^[1] These scores, in theory, are a quantitative measurement of the seriousness of a disease, and by extension, the risk of complications and death.^[3] The main issue of existing severity of illness systems is the lack of generalizability: SAPS 3 is one of the most common severity of illness scores, and its calibration varies based on geographical area, having the worst predictive results in Central and South America.^[4] This dependence is likely due to differences across ICUs in staffing, capacity for special diagnostic tests and interventions, variation in the culture of quality and patient safety, and others.^[2] An objective quantification of these differences is not possible without a validated severity of illness system developed from an international collaboration. An international consortium has come together to develop a family of open source illness severity scores for critical care, the Global Open Source Severity of Illness Score (GOSSIS).^[2] Up until now, the consortium has made available four different databases from Australia, Brazil, New Zealand, and the United States of America.

Data and its Processing

Several commercial and noncommercial ICU databases have been developed. These databases typically include patient demographics and aggregating information such as underlying disease, severity of illness, and unit- and hospital-specific information.^[5] The four databases used in this thesis are described below with the demographics of the final cohort presented on Table (1).

1. Australian and New Zealand intensive Care Society (ANZICS)

ANZICS is a binational intensive care database that includes one hundred thirty-eight intensive care units in Australia and New Zealand totaling more than 900,000 ICU stays. However, most ICUs are in Australia (with about 91% of ICU admissions being from Australia). The ratio of New Zealand to Australia data 1:10 is somewhat representative of the ratio of population of 1:5.^[6] The quality of the data was evaluated using the Directory of Clinical Databases (DoCDat) criteria, and it ranked as a high-quality ICU database.^[7]

For this thesis, the whole database was not used. Only the records from 2014 until 2015 were considered and the data was filtered through exclusion criteria similar to the other databases (Figure (1)).

2. eICU Collaborative Research Database v1.0

The eICU Collaborative Research Database contains data from multiple ICUs throughout the United States of America.^[8] It is collected from ICUs which have the Philips eICU platform. By 2013, the database contained over 1.5 million ICU stays, and incrementing about 400,000 patient records per year from over 180 subscribing hospitals in the country.^[5] However, for this thesis, only records from 2014 until 2015 were considered. Some further exclusion criteria was used to filter the data, shown in Figure (1).

3. Medical Information Mart for Intensive Care (MIMIC-III)

MIMIC-III is a freely accessible critical care database comprising information of patients admitted to critical care units at Beth Israel Deaconess Medical Center in Boston, Massachusetts. The data spans more than one decade of health records totaling to 49,785 hospital admissions. This database includes minute-by-minute physiological signals. [9] In order to make the dataset compatible with the other databases, the database was filtered through an exclusion criterion (Figure (1)).

4. ORganizational CCharactEriSTics in cRitical cAre (ORCHESTRA)

This Brazilian database includes 59,693 patients from 78 ICUs at 51 hospitals in 11 Brazilian states that account for one year of records (2013). This dataset was screened for missing data, outliers, and logical errors. Missing data on patient's characteristics was imputed using the normal category.^[10] Specifics about the database can be found on Soares M. *et al* including the imputation method used, exclusion criteria, and specific distribution of the ICUs throughout the hospitals and states. ^[10] Note that exclusion criteria were applied before acquisition of the data.

Table (1). Demographics of the four databases

	ANZICS	eICU	MIMIC	ORCHESTRA
n	266136	122893	38139	59693
age (mean (std))	61.55 (17.86)	61.96 (16.63)	63.81 (17.67)	62.33 (19.33)
height (mean (std))	169.26 (11.43)	169.40 (13.90)	169.56 (11.75)	165.89 (10.83)
hospital_los_days (mean (std))	14.41 (72.63)	6.82 (9.07)	9.92 (10.71)	15.63 (29.06)
icu_los_days (mean (std))	3.02 (5.08)	2.95 (3.96)	4.10 (6.04)	5.01 (9.13)
pre_icu_los_days (mean (std))	3.40 (71.00)	0.85 (3.80)	1.04 (3.30)	2.65 (42.96)
weight (mean (std))	83.16 (23.87)	84.09 (26.98)	81.59 (22.90)	74.44 (19.25)
elective_surgery (n (%))				
0	147616 (55.56)	100757 (81.99)	32099 (84.16)	43041 (72.10)
1	118084 (44.44)	22136 (18.01)	6040 (15.84)	16652 (27.90)
gender (n (%))				
F	113519 (42.66)	56478 (45.97)	16554 (43.40)	29911 (50.12)
M	152596 (57.34)	66383 (54.03)	21585 (56.60)	29773 (49.88)
hospital_death (n (%))				
0	244076 (91.82)	112084 (91.20)	33938 (88.99)	51112 (85.62)
1	21731 (8.18)	10809 (8.80)	4201 (11.01)	8581 (14.38)
icu_death (n (%))				
0	251602 (94.75)	116019 (94.41)	35174 (92.23)	53970 (90.41)
1	13945 (5.25)	6874 (5.59)	2965 (7.77)	5722 (9.59)
pregnant (n (%))				
0	38393 (98.20)	0 (nan)	1929 (98.77)	0 (nan)
1	702 (1.80)	0 (nan)	24 (1.23)	0 (nan)
smoking_status (n (%))				
Current Smoker	18809 (23.69)	0 (nan)	18043 (47.31)	0 (nan)
Ex-Smoker	31731 (39.96)	0 (nan)	274 (0.72)	0 (nan)
Never Smoked	28870 (36.36)	0 (nan)	10870 (28.50)	0 (nan)
Unknown	0 (0.00)	0 (nan)	8952 (23.47)	0 (nan)
teaching_hospital (n (%))				
0	90228 (33.90)	84715 (68.93)	0 (0.00)	0 (nan)
1	175908 (66.10)	38178 (31.07)	38139 (100.00)	0 (nan)

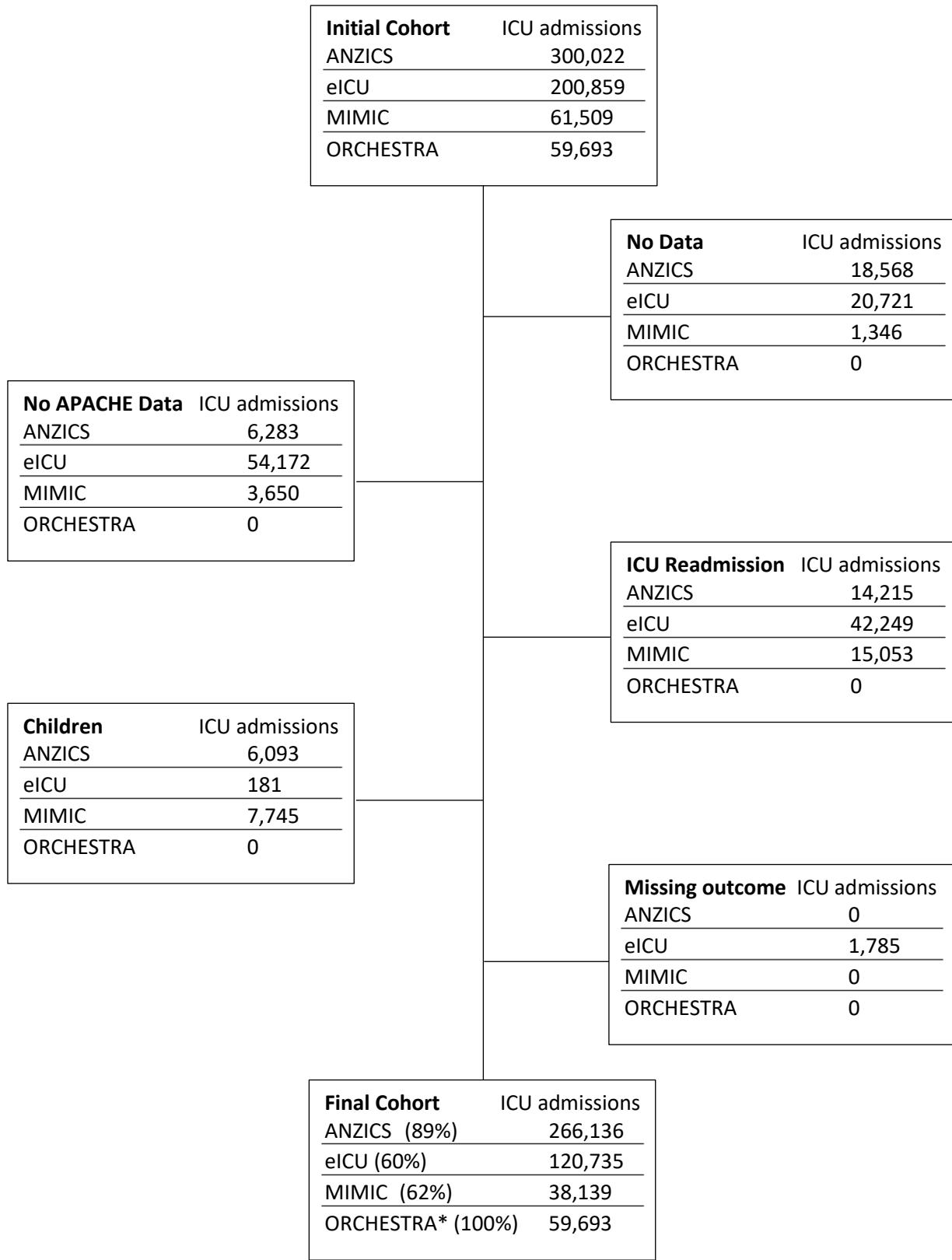


Figure (1). Flowchart of patient inclusion.

*ORCHESTRA had exclusions applied before acquisition.

Variables of interest

The great majority of the variables have no significant variability within the databases: histograms used for comparison found in Appendix. However, some stand out due to the difference in distribution between the databases.

1. Similar Distributions

As mentioned previously, many of the variables extracted from the databases have similar distributions and completeness (age and white blood cell count used as examples Figure (2); Table (2)). However, some distributions have subtle differences that can be insightful, and their generalization to patients and hospitals not included in the training set of the model can be misleading and incorrect due to the reasons described in the subsequent sections.

Table (2). Statistical measures of a subset of similar variables.

	anzics	eicu	mimic	orchestra
age_avg	61.6	62.0	63.8	62.3
age_med	64.8	64	65.7	65
age_std	17.9	16.6	17.7	19.3
d1_wbc_min_avg	11.3	11.4	11.0	
d1_wbc_min_med	10.2	10	9.9	
d1_wbc_min_std	7.3	8.4	7.9	

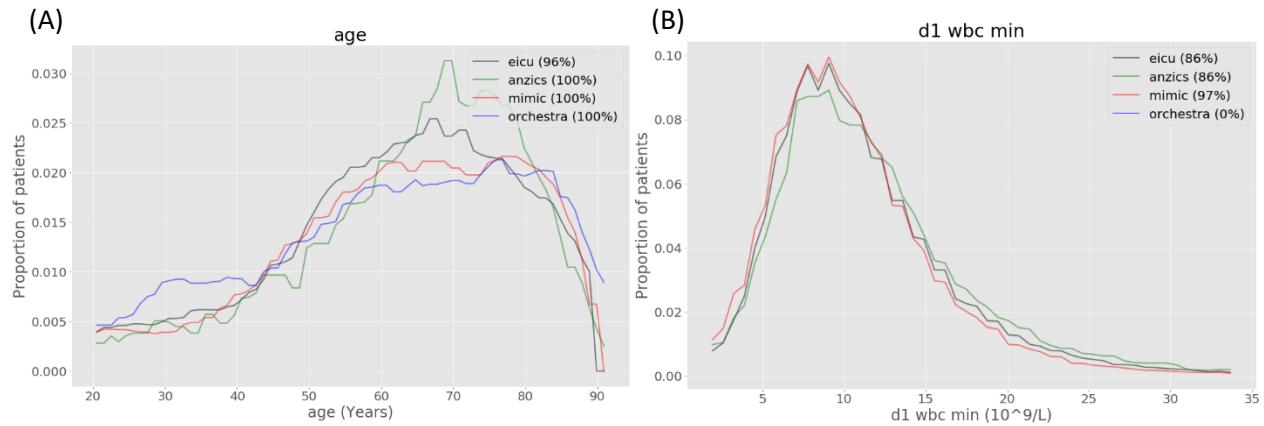


Figure (2). Plot of the patient distribution for age and white blood cell count. The legend reads as: database (% of database with available measurements).

2. Selection Bias

An interesting pattern was evident in several of the variables (Figure (3)). ORCHESTRA patients had a tendency to have variables values closer to “normal” levels. Some of the variables that showed this phenomenon had higher rates of completeness in ORCHESTRA than in other databases, and consequently the effect may be attributable to differences in practice. For example, in ORCHESTRA, the platelets measurement was available for 83% of the patients within the first hour of stay in the ICU, while eICU and MIMIC only 18% and 28% were available, respectively (Figure (3A)). This could mean that the platelet measurements in the North American hospitals are only acquired for select patients with specific conditions driving the distribution to more extreme values. However, even among variables with similar completeness (such as mean blood pressure), ORCHESTRA patients appear to have values closer to reference levels (Figure (3B)). This may imply that these variables have been able to capture a selection bias introduced by Brazilian hospitals of healthier patients admitted into the ICU.

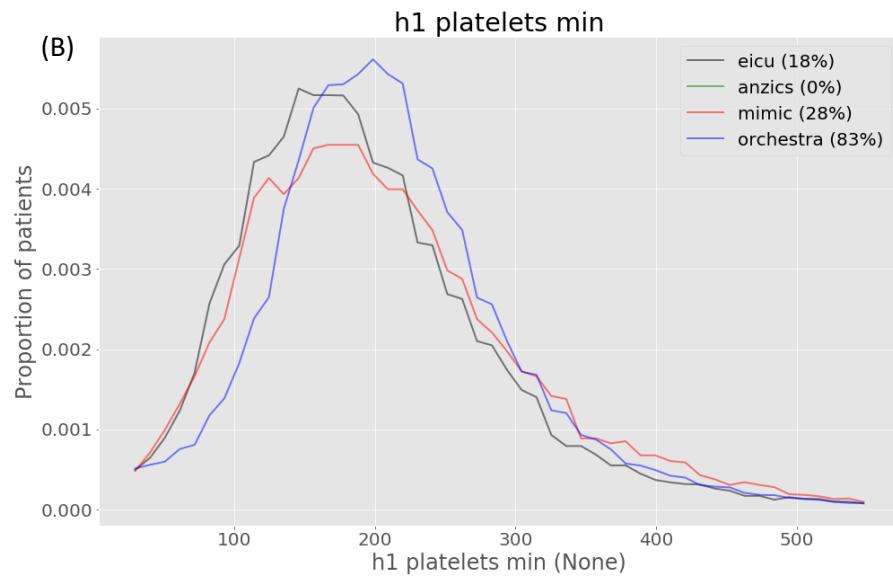
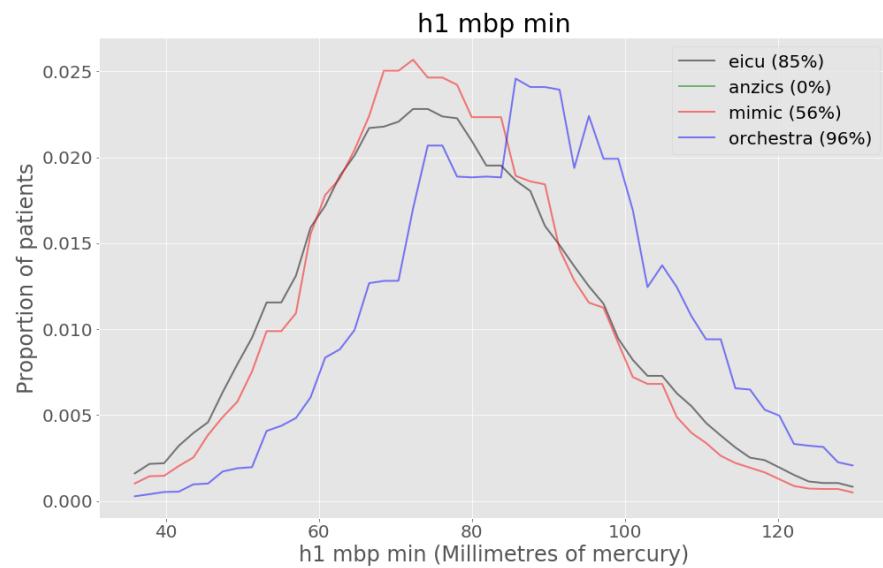


Figure (3). (A) Distribution of a variable containing similar completeness in eICU and ORCHESTRA

(B) Distribution of a variable containing distinct completeness throughout the databases.

3. Hospital Practices

The maximum Arterial PO₂ across the first day or across the first hour has a distinctive bimodal distribution in MIMIC and not in other databases (Figure (4)). One hypothesis for this unique distribution is that patients who undergo intubation get an excess of O₂ prior to any extubation, and that MIMIC contains a large number of surgical patients who undergo extubation during the first day. This hypothesis is partly substantiated when noting that the minimum O₂ level exhibits this bimodal distribution in the first hour but not for the whole day of measurements (Figure (4)(A)). To further analyze this hypothesis, we stratified the patients based on the ventilation flag (Figure (5)). For MIMIC, this flag indicates invasive ventilation, and for eICU this flag indicates both invasive and non-invasive ventilation. Those patients who were mechanically ventilated on the MIMIC database showed the unique distribution within the first hour in both minimum and maximum O₂ measurements. As expected, those without mechanical ventilation did not show the bimodal distribution. It is important to point out that MIMIC includes data from a single hospital. Due to this, we can easily detect a conventional practice within a single institution which would otherwise be masked by other hospitals included in the database.

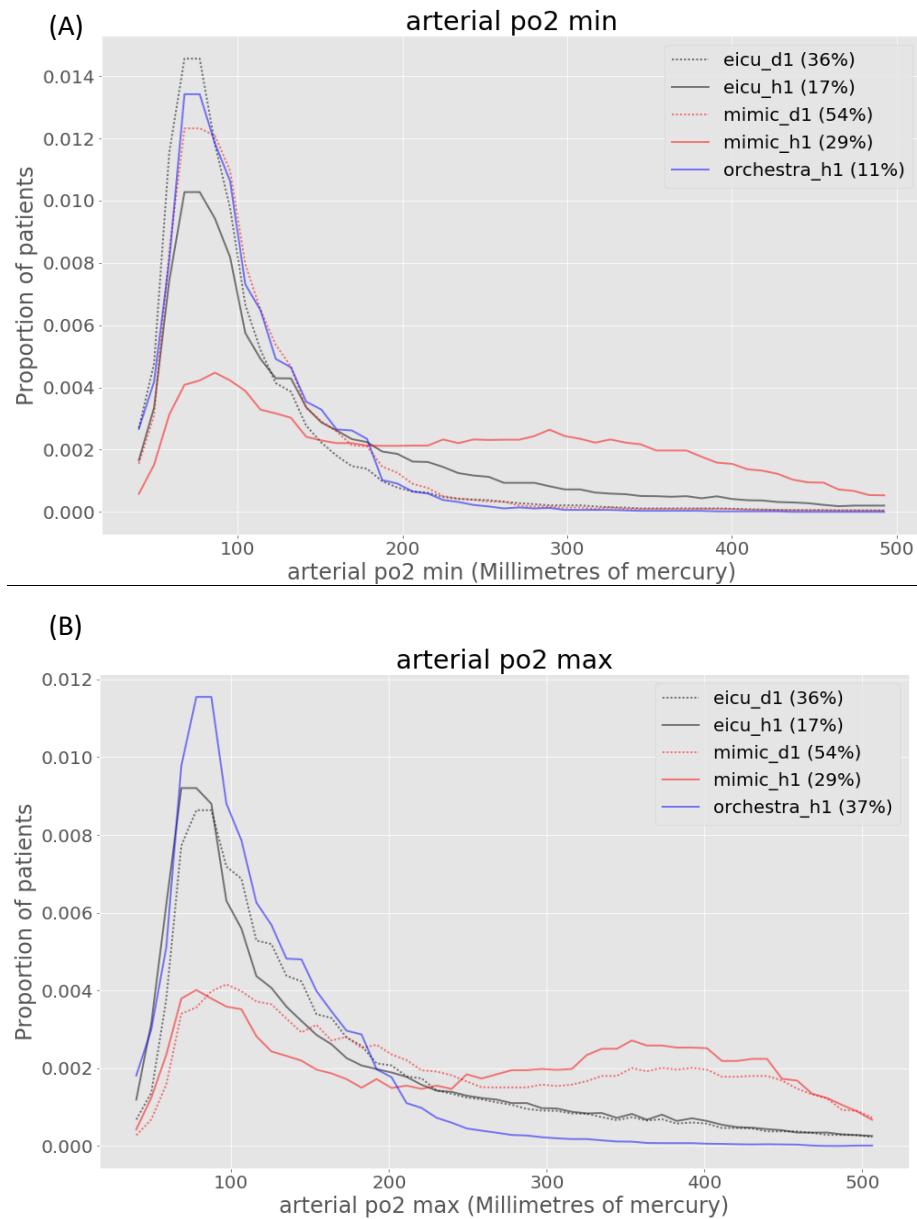


Figure (4). Arterial PO₂ max and min measurements in one hour and one day.

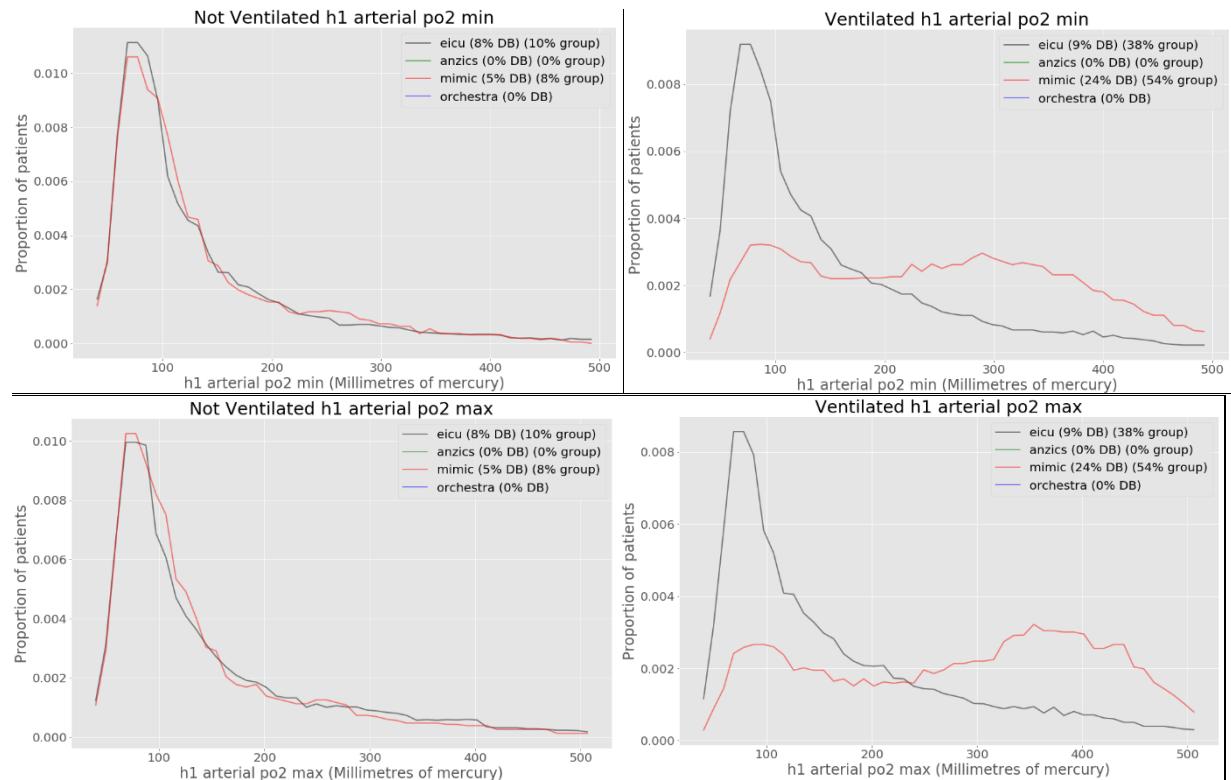


Figure (5). Arterial PO₂ max and min measurements in one hour and one day stratified by mechanical ventilation flag.

4. Practices and Cohort

Selection bias, medical practice differences, and other factors can be visible within the distributions of the variables of interest. This is why it is so important to have a severity of illness score that will not assume uniformity across hospitals and/or countries. It is clear from this review of the databases that practice variation which occurs across geographically distinct institutions can result in dissimilar data distributions.

Predictive Model

In order to test the generalizability of each database to the other, we developed a predictive model of in-hospital mortality. a logistic regression model was created using one of the databases as the training set, and testing on a different database.

1. Covariates and Data Imputation

Due to the differences in data collection between the databases, three different lists of covariates of interest were selected, (SetA) those present in ANZICS, eICU, and MIMIC excluding APACHE variables (Table (4)), (SetB) APACHE variables present in ANZICS, eICU, and MIMIC (Table (5)), and (SetC) variables present in eICU, MIMIC, and ORCHESTRA (Table (6)). Given that APACHE variables depend on the APACHE score, they were treated separately from the rest of the variables.

A single imputation method was used with dummy variable control using the average (continuous variables) or the most common category (categorical variables) to impute the missing data.

Table (4). (SetA) ANZICS, eICU, and MIMIC model covariates and percentage completion

	anzics	eicu	mimic		anzics	eicu	mimic
age	100	96.46	100	d1_platelets_min	77.19	85.46	97.36
bmi	31.32	96.71	41.58	d1_potassium_max	97.24	90.59	98.47
d1_creatinine_max	97	89.83	98.13	d1_potassium_min	92.35	90.59	98.47
d1_creatinine_min	90.71	89.83	98.13	d1_resprate_max	99.61	91.81	99.68
d1_diasbp_max	98.21	98.99	99.7	d1_resprate_min	99.46	91.81	99.68
d1_diasbp_min	98.65	98.99	99.7	d1_sodium_max	97.41	89.82	98.18
d1_glucose_max	92.51	94.07	98.15	d1_sodium_min	92.49	89.82	98.18
d1_glucose_min	89.53	94.07	98.16	d1_sysbp_max	99.86	98.99	99.71
d1_hco3_max	94.96	84.39	97.6	d1_sysbp_min	99.78	98.99	99.71
d1_hco3_min	90.23	84.39	97.6	d1_temp_max	99.69	7.95	98.18
d1_heartrate_max	100	99.02	99.78	d1_temp_min	99.42	7.95	98.18
d1_heartrate_min	100	99.02	99.78	d1_wbc_max	96.61	86.19	97
d1_hemoglobin_max	82.76	87.34	97.41	d1_wbc_min	89.46	86.19	97
d1_hemoglobin_min	77.66	87.34	97.41	elective_surgery	99.84	100	100
d1_hematocrit_max	94.33	87.71	98.13	gender	99.99	99.97	100
d1_hematocrit_min	89.51	87.71	98.13	height	31.6	98.74	41.71
d1_mbp_max	99.84	99	99.78	hospital_death	100	100	100
d1_mbp_min	99.78	99	99.78	pre_icu_los_days	99.59	100	100
d1_platelets_max	82.73	85.46	97.36	weight	38.04	97.55	87.53

Table (5). (SetB) APACHE model covariates and percentage completion

	anzics	eicu	mimic	hospital_death	100	100	100
albumin_apache	93.58	39.05	35.45	map_apache	99.91	100	99.78
bilirubin_apache	90.08	35.33	42.86	paco2_apache	76.55	23.72	56.97
bun_apache	96.55	79.83	99.33	paco2_for_ph_apache	76.16	23.72	56.97
creatinine_apache	97.14	80.25	99.35	pao2_apache	76.52	23.72	56.97
fio2_apache	76.57	23.72	39.61	ph_apache	76.17	23.72	56.97
gcs_eyes_apache	96.96	98.93	99.48	resprate_apache	99.63	100	99.65
gcs_motor_apache	96.97	98.93	99.07	sodium_apache	97.55	80.57	99.35
gcs_verbal_apache	96.96	98.93	99.1	temp_apache	99.75	96.92	98.08
glucose_apache	92.69	88.93	99.59	urineoutput_apache	92.18	50.27	98.38
heart_rate_apache	100	100	99.78	ventilated_apache	100	100	100
hematocrit_apache	94.68	78.49	99.38	wbc_apache	96.79	76.21	98.75

Table (6). (SetC) eICU (E), MIMIC (M), and ORCHESTRA (O) model covariates and percentage completion

	E	M	O		h1_heartrate_max	89.3	56.96	96.7
age	96.46	100	100	h1_lactate_max	8.67	19.51	44.27	
bmi	96.71	41.58	58.06	h1_mbp_min	85.91	56.03	96.51	
elective_surgery	100	100	100	h1_pao2fio2ratio_min	11.95	10.79	9.03	
gender	99.97	100	99.98	h1_platelets_min	18.09	28.82	83.25	
h1_arterial_pco2_max	17.52	31.5	37.41	h1_resprate_max	80.69	57.65	95.94	
h1_arterial_pco2_min	17.52	31.5	11.63	h1_sysbp_min	85.86	56.18	96.56	
h1_arterial_ph_max	17.16	31.5	37.56	h1_temp_max	5.06	53.42	95.11	
h1_arterial_ph_min	17.16	31.5	11.75	h1_wbc_max	17.76	27.27	81.67	
h1_arterial_po2_max	17.53	31.5	37.43	height	98.74	41.71	58.66	
h1_arterial_po2_min	17.53	31.5	11.61	hospital_death	100	100	100	
h1_bilirubin_max	7.9	9.75	29.36	pre_icu_los_days	100	100	99.8	
h1_CREATININE_max	19.08	25.84	82.73	weight	97.55	87.53	65.16	
h1_diasbp_min	85.86	56.18	96.51					

2. Logistic Regression

As mentioned before, the logistic regression model was trained with the processed dataset of one of the databases and tested against the processed dataset of a different database. The dependent variable to be predicted was in-hospital mortality. Three models were developed using each database as a training set, one for each covariate set (SetA, SetB, SetC), for a total of 9 models. Due to the bimodal distributions caused by the data collection process for APACHE variables (i.e. minimum and maximum values collapsed into a single covariate), we built additional models for SetB covariates using B-splines on manually identified covariates. Table (7) lists the various configurations used for developing and evaluating models.

Table (7). Model configurations

	Training	Testing
SetA	ANZICS	eICU, MIMIC
	eICU	ANZICS, MIMIC
	MIMIC	ANZICS, eICU
SetB	ANZICS	eICU, MIMIC
	eICU	ANZICS, MIMIC
	MIMIC	ANZICS, eICU
SetC	eICU	MIMIC, ORCHESTRA
	MIMIC	eICU, ORCHESTRA
	ORCHESTRA	eICU, MIMIC

3. Scoring the Models

The area under ROC curve was used to evaluate the performance of the model by predicting in-hospital mortality and is reported on the legend of Figures 6-9. We constructed calibration curves, which assessed the concordance between predicted and observed outcomes across deciles of risk (Figures (6-9)).

(SetA) ANZICS, eICU, and MIMIC variables

Given the low frequency of in-hospital deaths, there should be a strong bias towards lower probability predictions. However, this is not true when predicting on eICU using either ANZICS or MIMIC as the training set (Figure (6)). In general, eICU seems to be the best predictor for other databases. Nevertheless, the score and calibration are very low, as expected (Figure (6)).

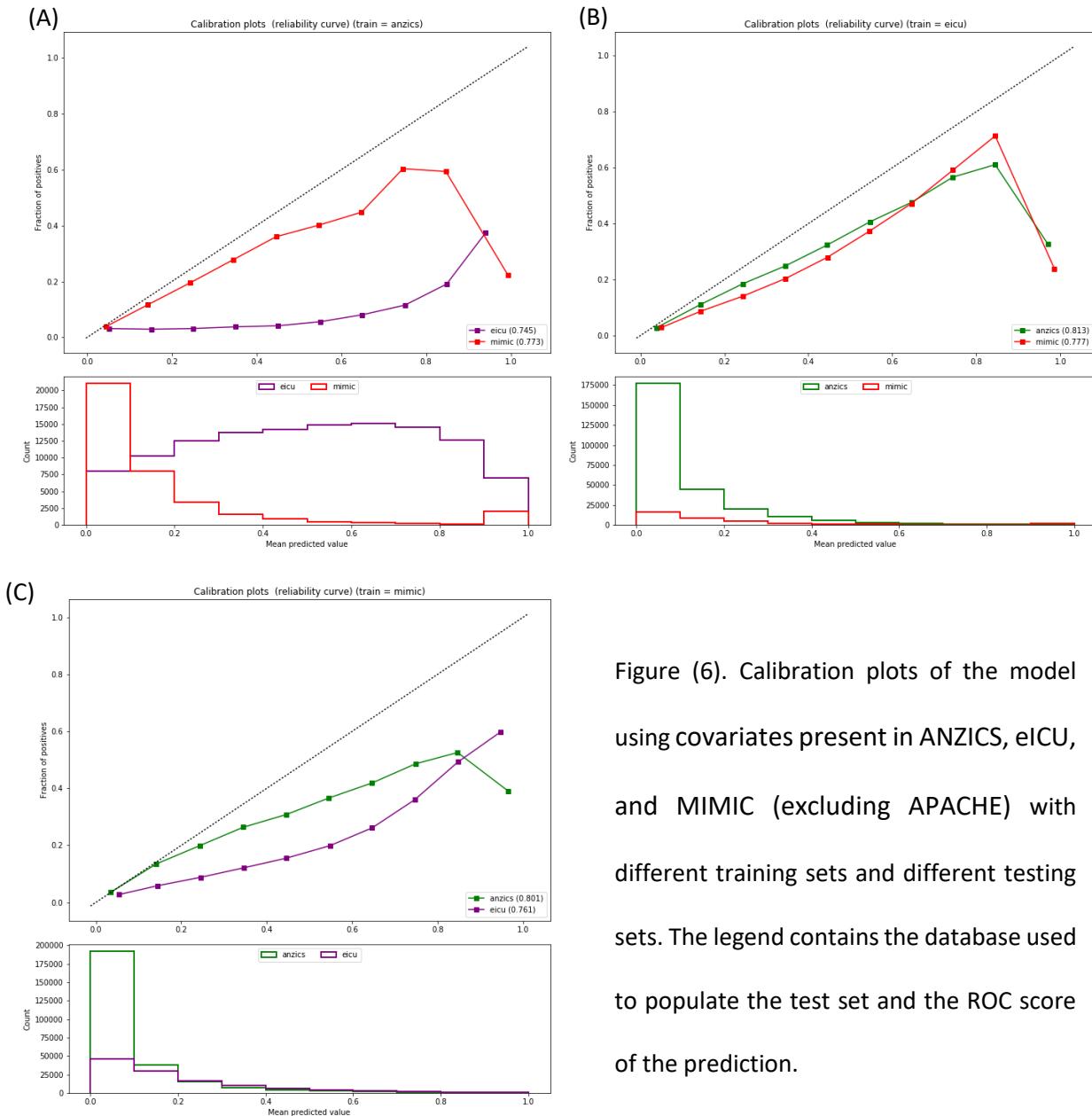


Figure (6). Calibration plots of the model using covariates present in ANZICS, eICU, and MIMIC (excluding APACHE) with different training sets and different testing sets. The legend contains the database used to populate the test set and the ROC score of the prediction.

(SetB) APACHE variables (not in ORCHESTRA) with and without B-splines

B-splines model a single covariate with multiple coefficients allowing a nonlinear relationship between the covariate and the dependent variable. B-splines were used to represent APACHE variables that had bimodal distributions. However, the coefficients of the B-splines of glucose, temperature, and mean arterial pressure were about 10-fold greater than the rest for the model trained using ANZICS (Appendix). This implies that the model is poorly specified, which may explain why the distribution of prediction probabilities is not similar to the expected one (described on the previous model) (Figure (7)). To address this, we repeated the analysis without B-splines, and achieved more reasonable calibrations though the AUROCs were generally lower (Figure (8)).

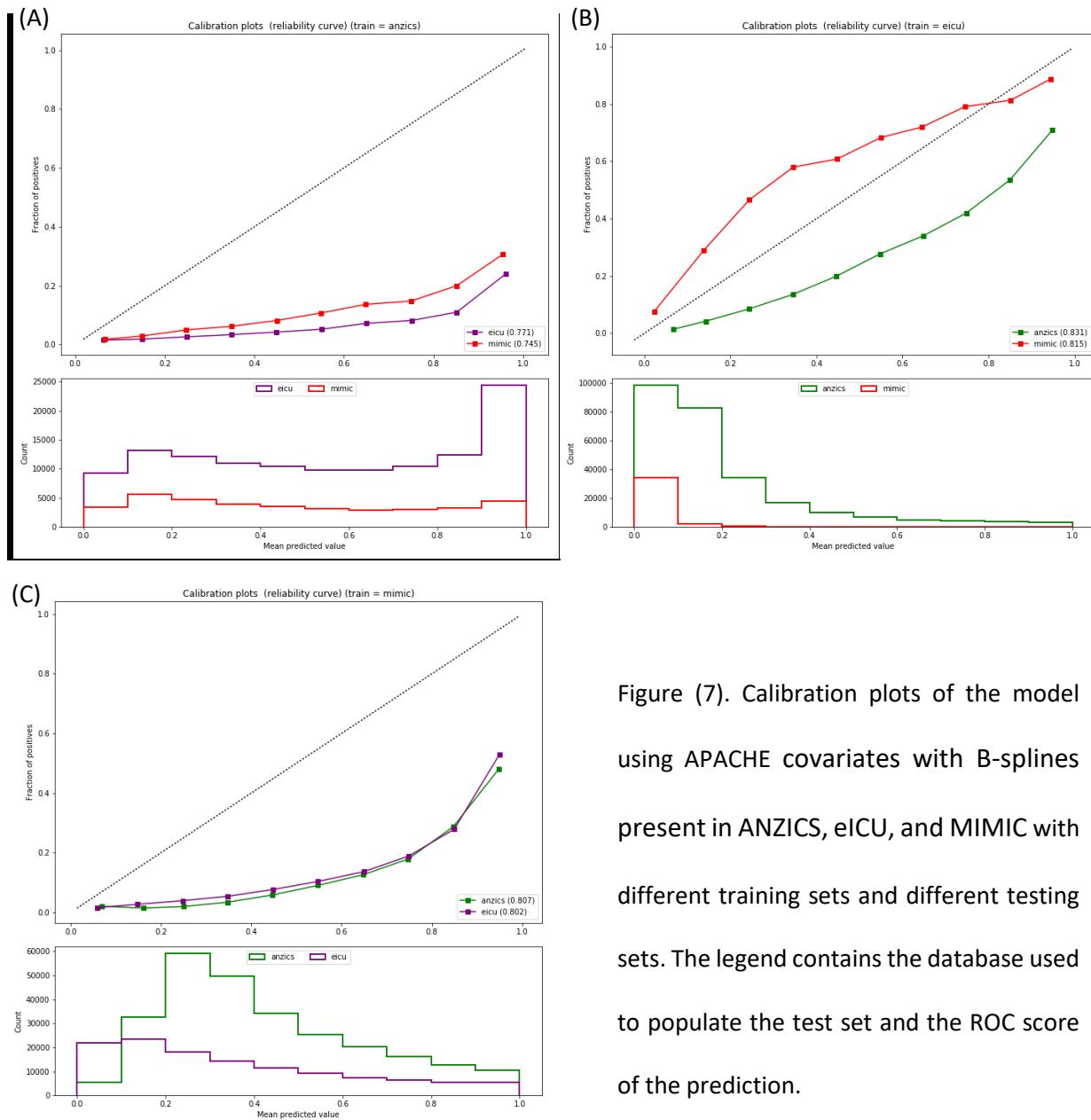


Figure (7). Calibration plots of the model using APACHE covariates with B-splines present in ANZICS, eICU, and MIMIC with different training sets and different testing sets. The legend contains the database used to populate the test set and the ROC score of the prediction.

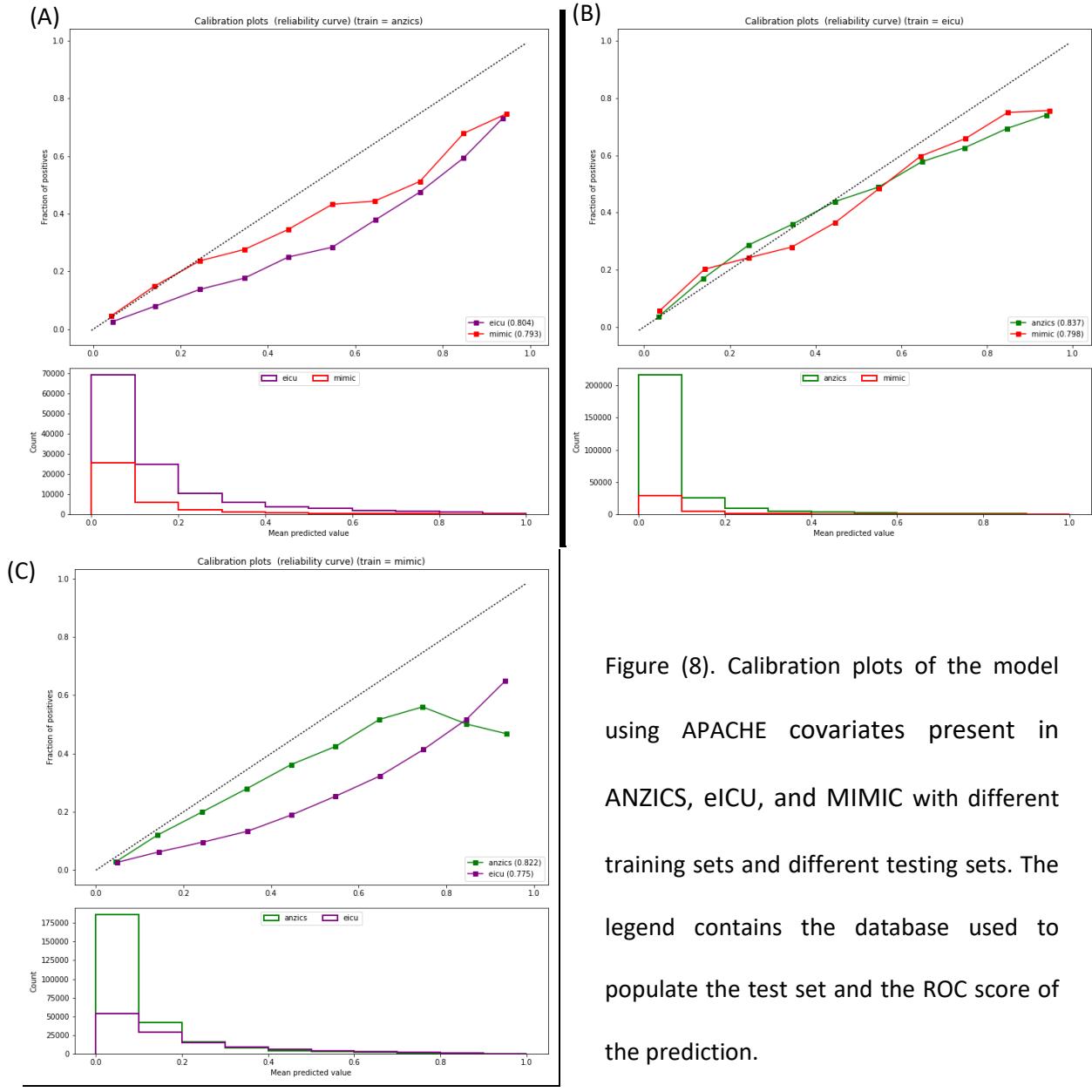


Figure (8). Calibration plots of the model using APACHE covariates present in ANZICS, eICU, and MIMIC with different training sets and different testing sets. The legend contains the database used to populate the test set and the ROC score of the prediction.

(SetC) eICU, MIMIC, and ORCHESTRA variables

Similar to previous discussion of other models, the general distribution of prediction probabilities follows what is expected. However, when we train on ORCHESTRA, the prediction power and calibration are at their lowest. This could be for various reasons: (1) due to the selection bias discovered before, the ORCHESTRA variables are not generalizable to patients in other databases, and (2) given that the completeness of some of the ORCHESTRA variables is substantially different to the other databases, the “dummy” variables do not capture the same missing data mechanisms and thus do not predict well when applied to the other databases.

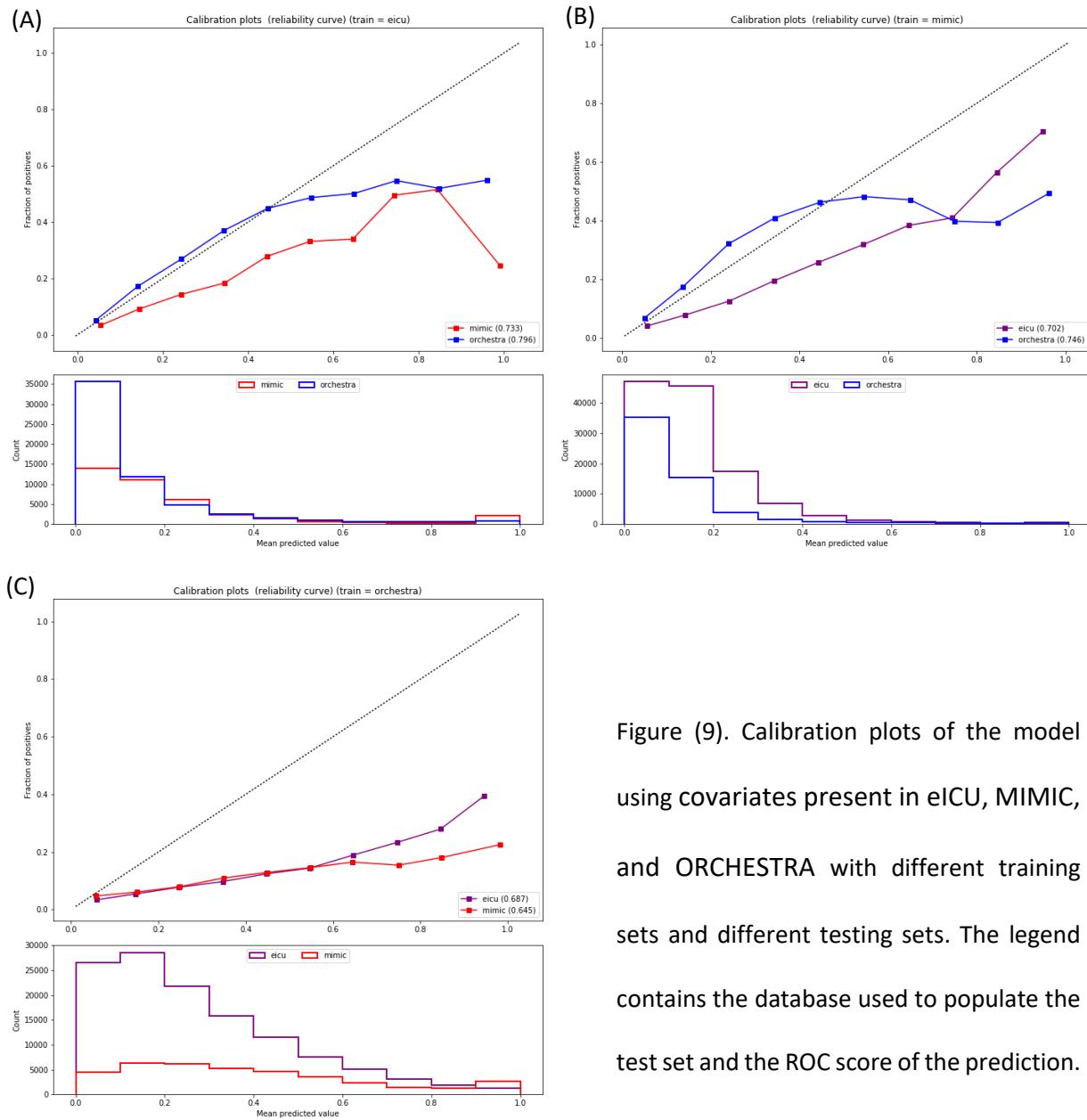


Figure (9). Calibration plots of the model using covariates present in eICU, MIMIC, and ORCHESTRA with different training sets and different testing sets. The legend contains the database used to populate the test set and the ROC score of the prediction.

Conclusions and Future work

Electronic health records and subsequently derived databases are becoming increasingly present internationally. [11] The data contained in these databases has the opportunity to be used in hospital benchmarking in order to identify policies which have beneficial effects on patient outcomes. However, the source of data of previous models came mainly from high income countries. This thesis examined international data and compared common variables to assess differences in distributions. These differences, in their great majority, may be attributed to practice and selection bias, and should be considered when building models. Future models should focus on the incorporation of the differences in the underlying data, such as Hierarchical models.

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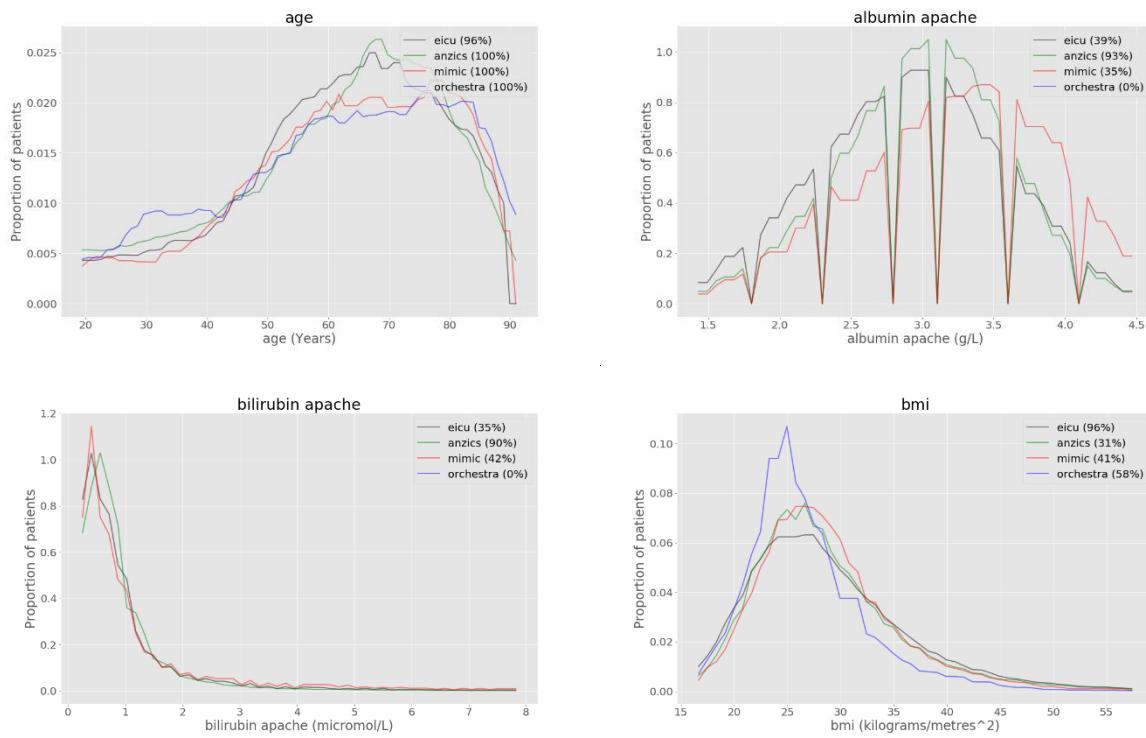
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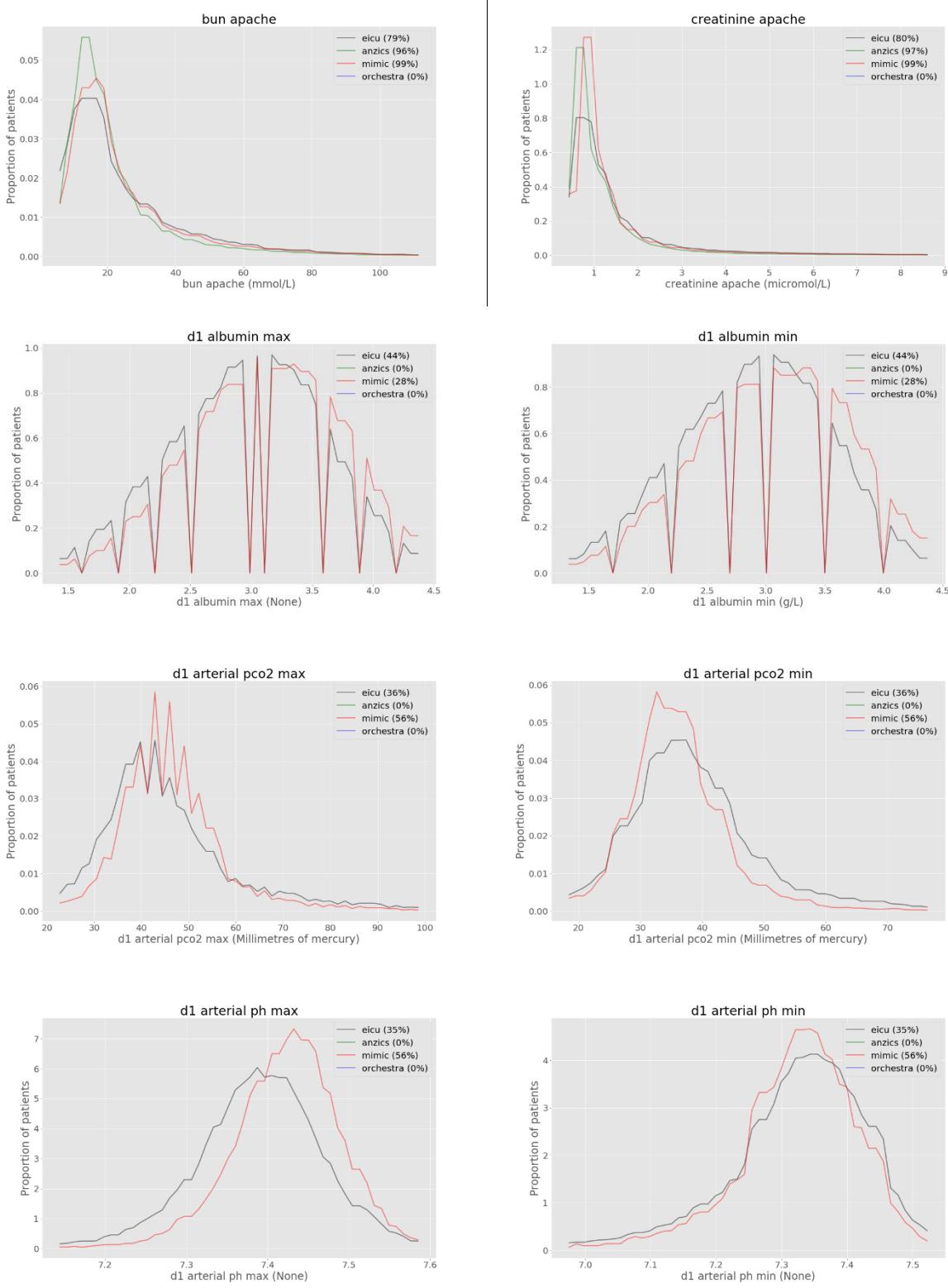
Appendix

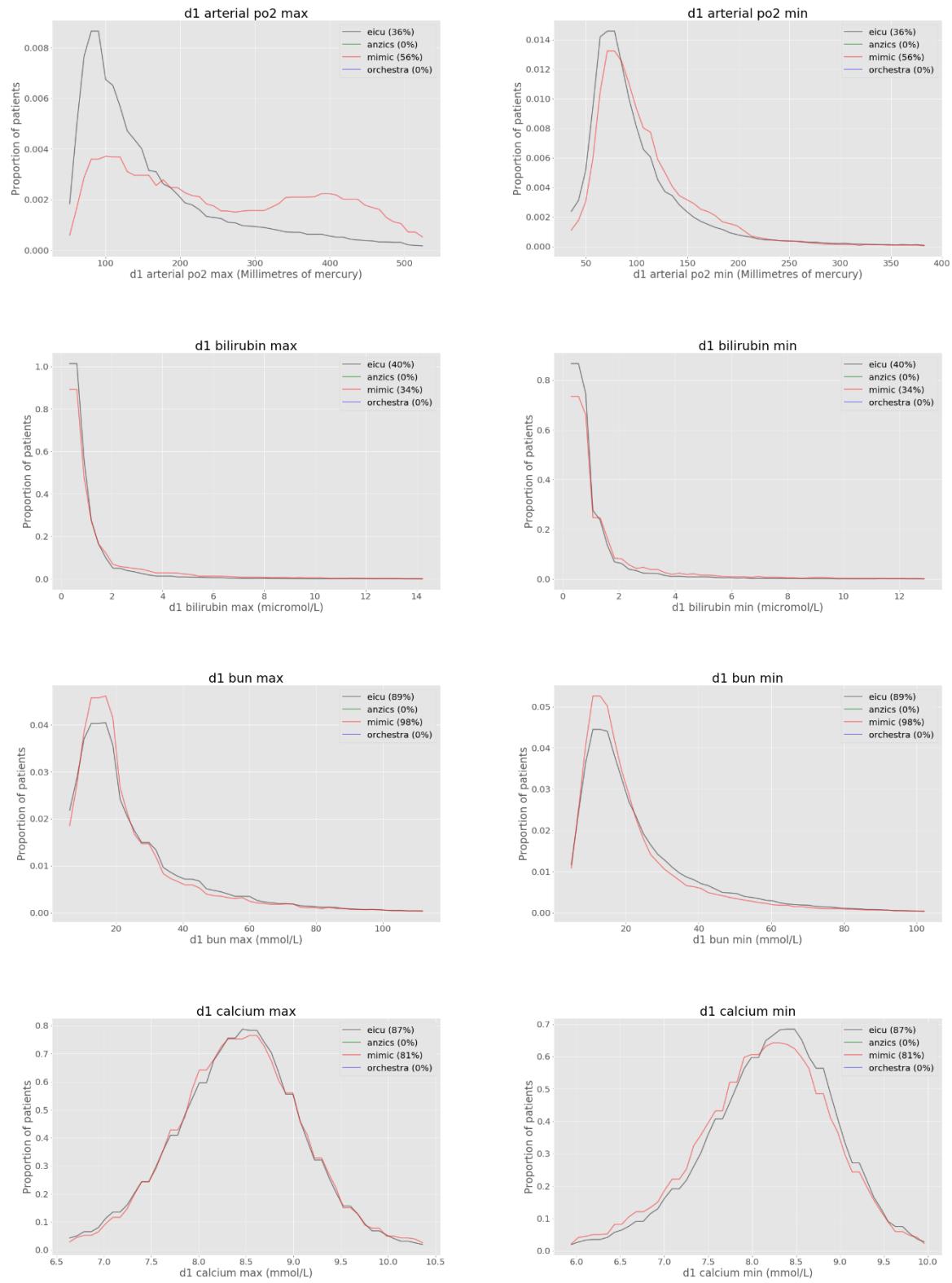
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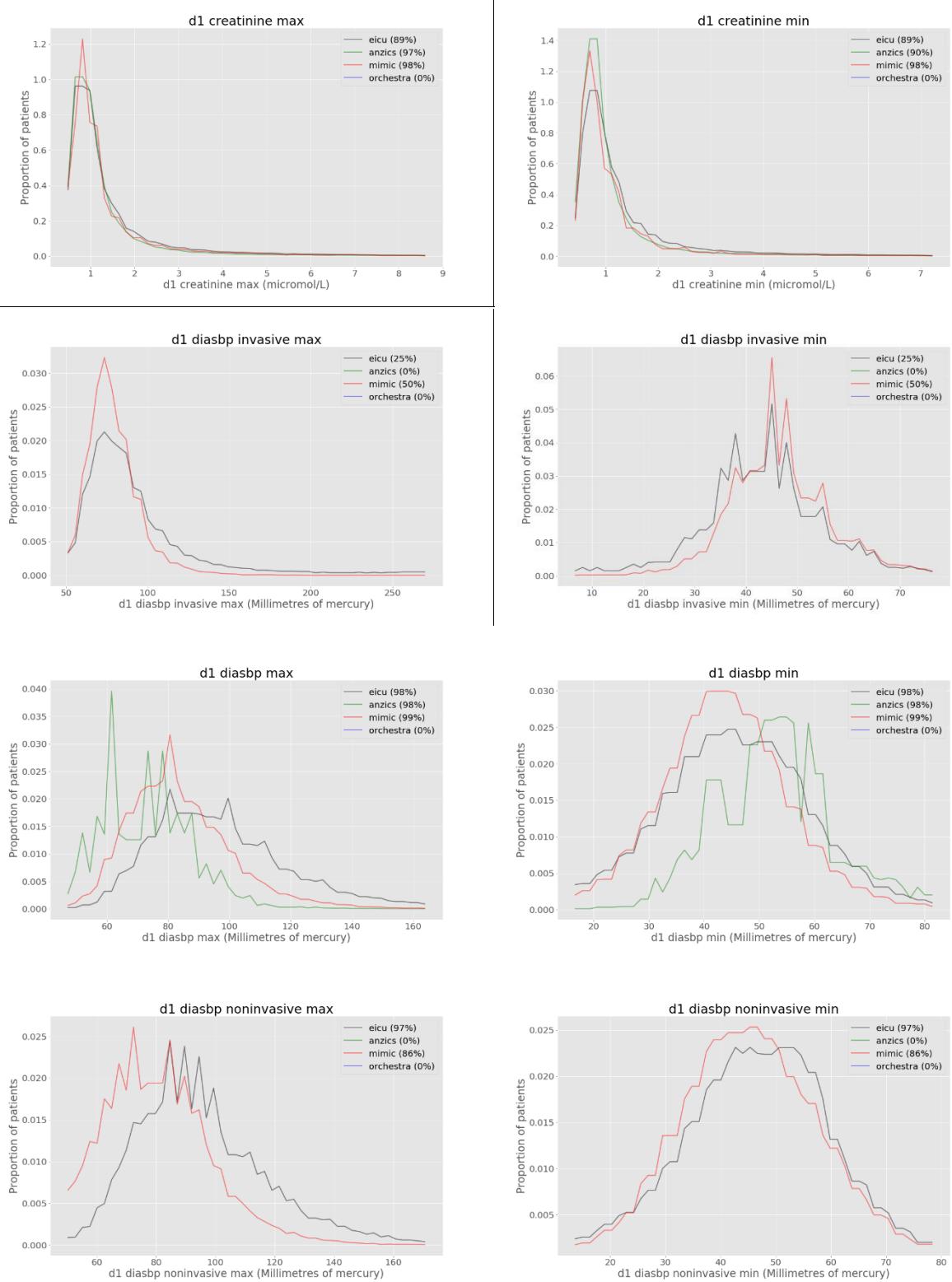
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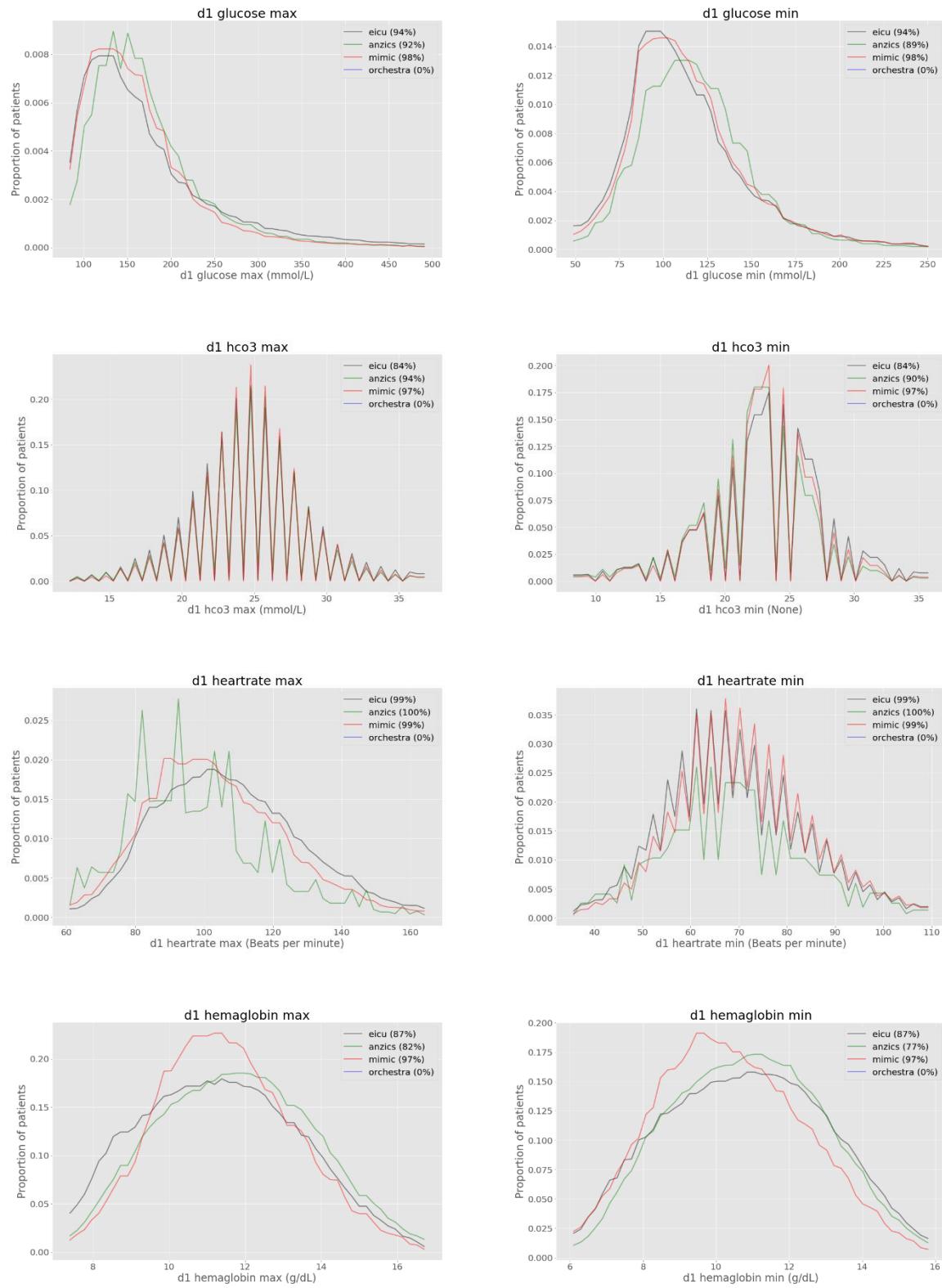
Histograms

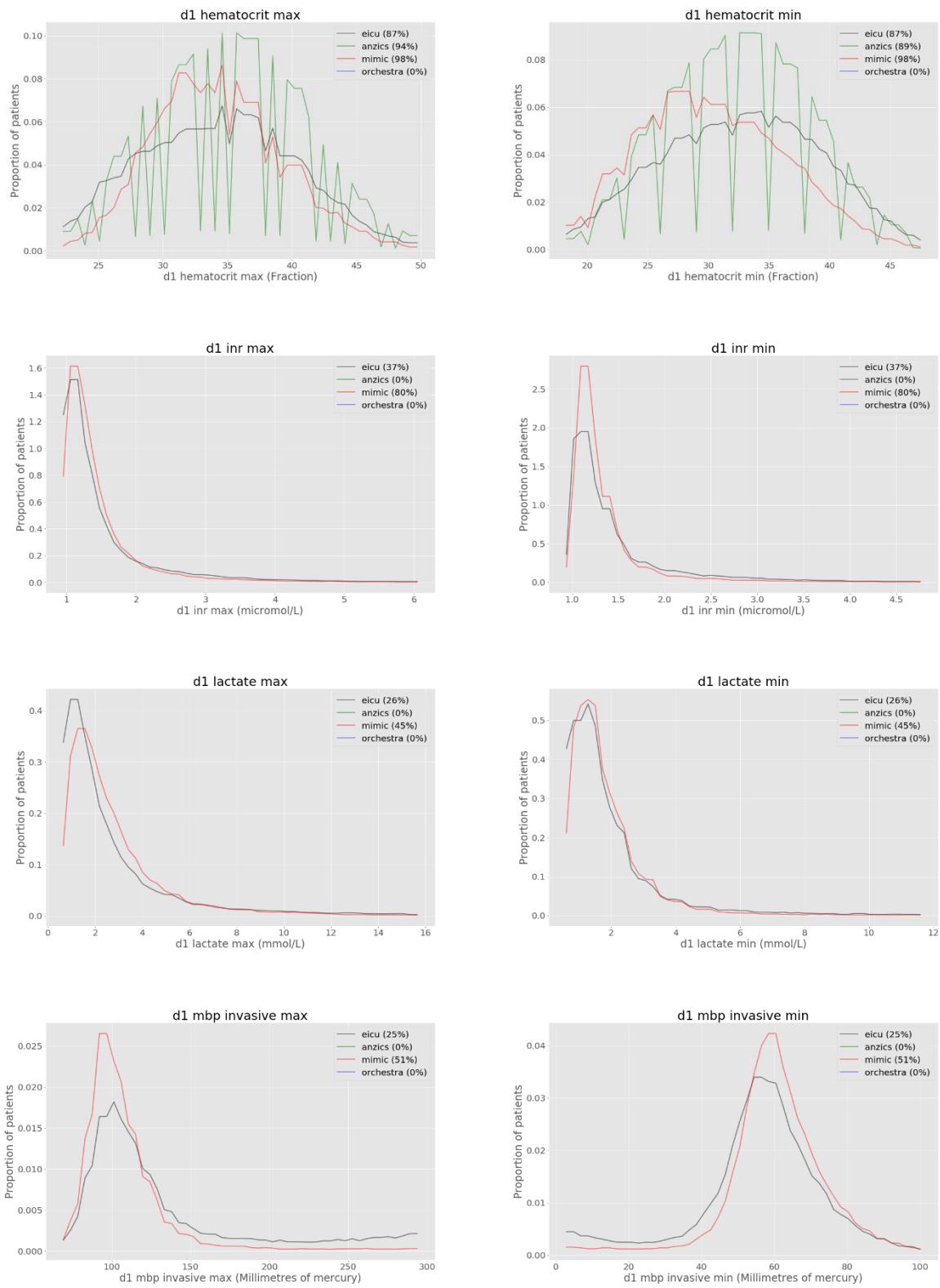


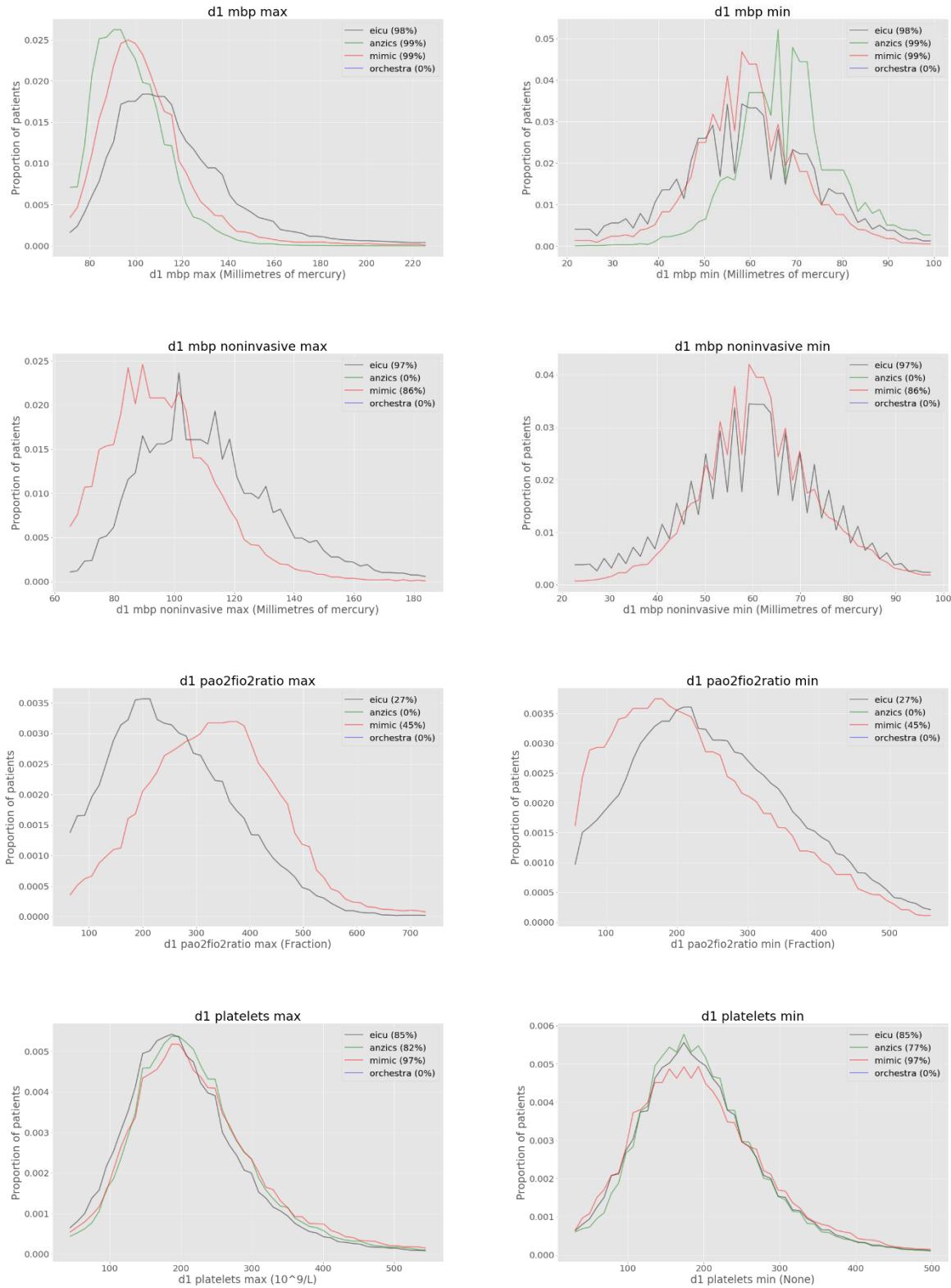


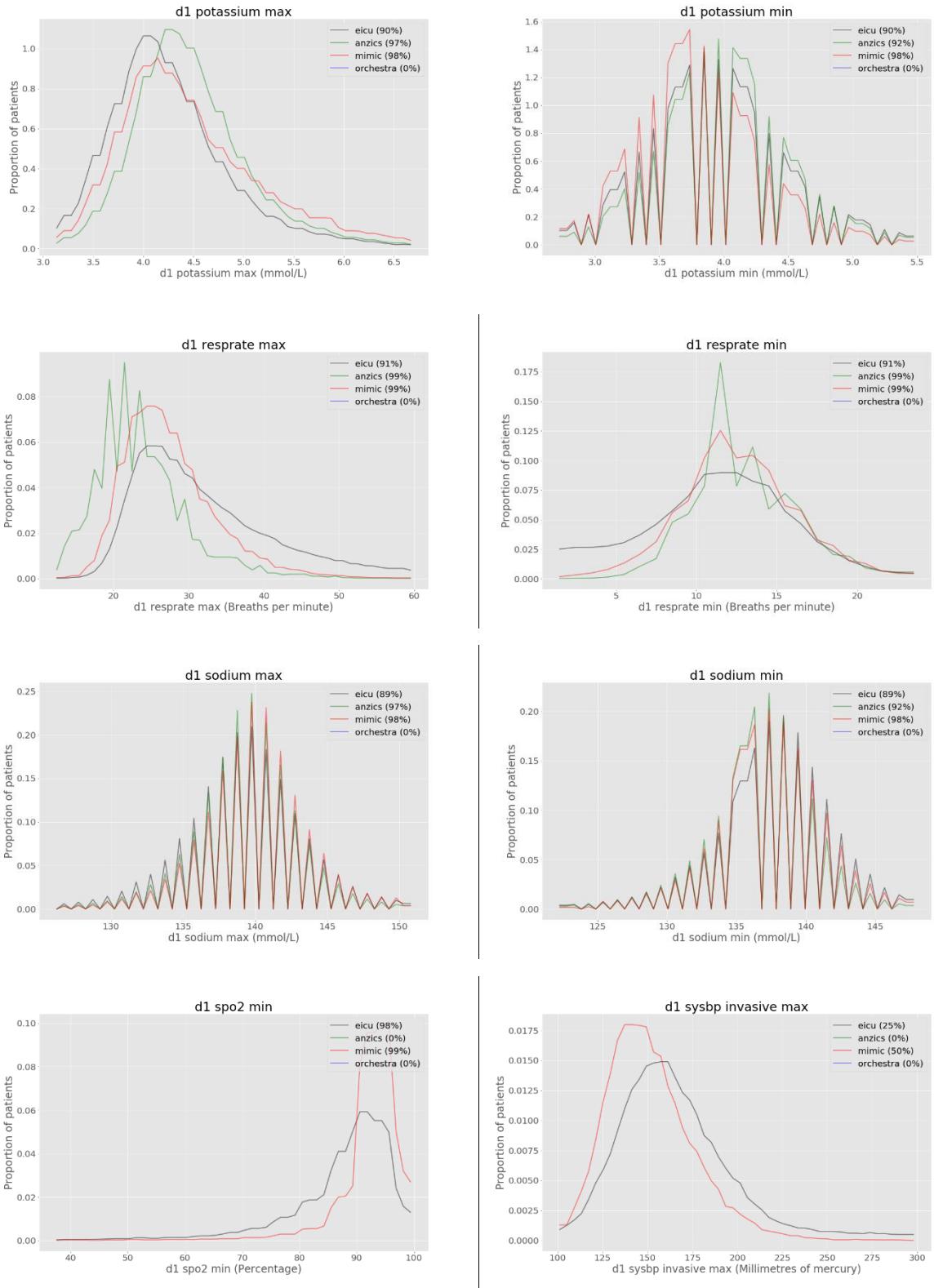


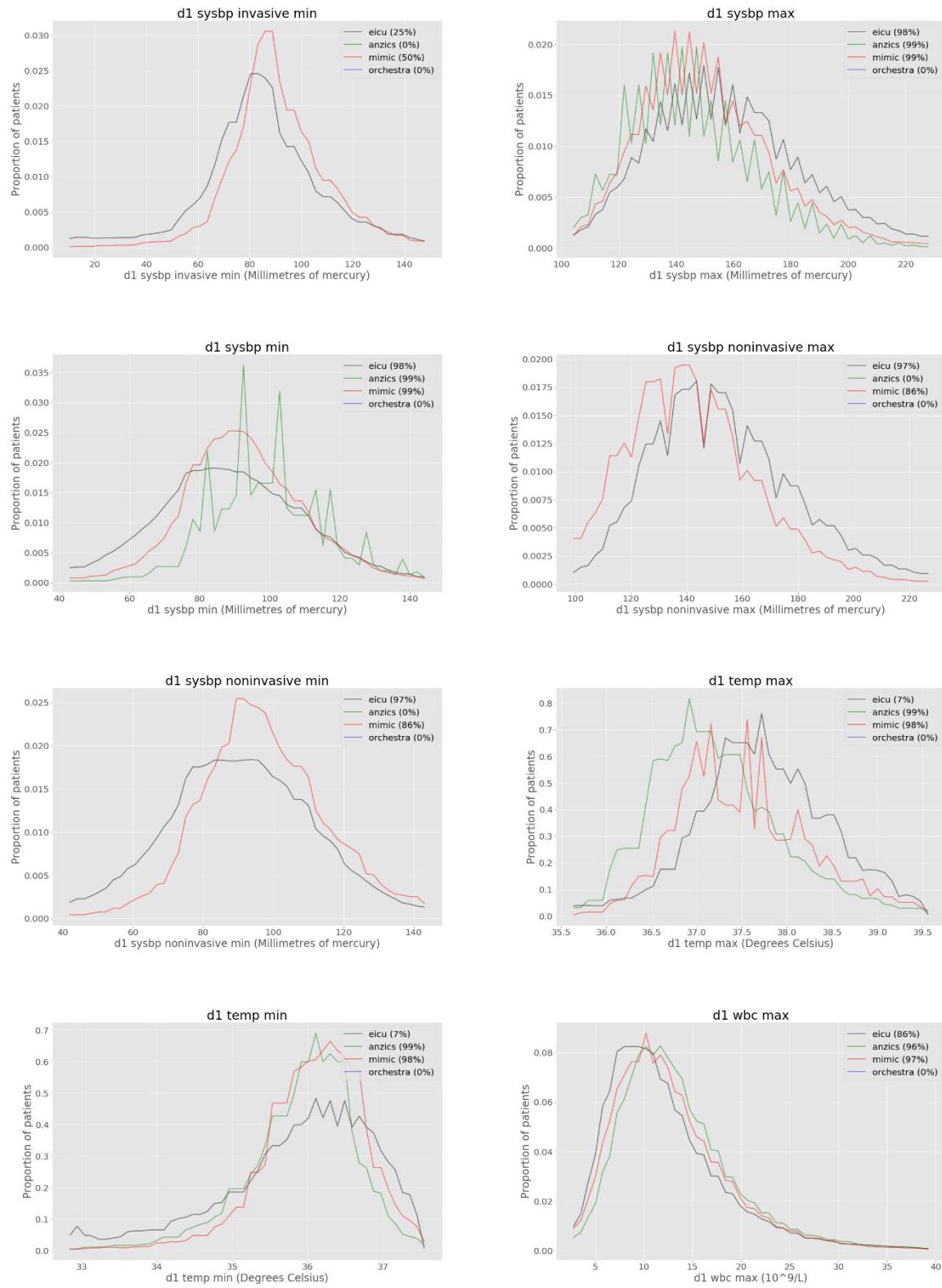


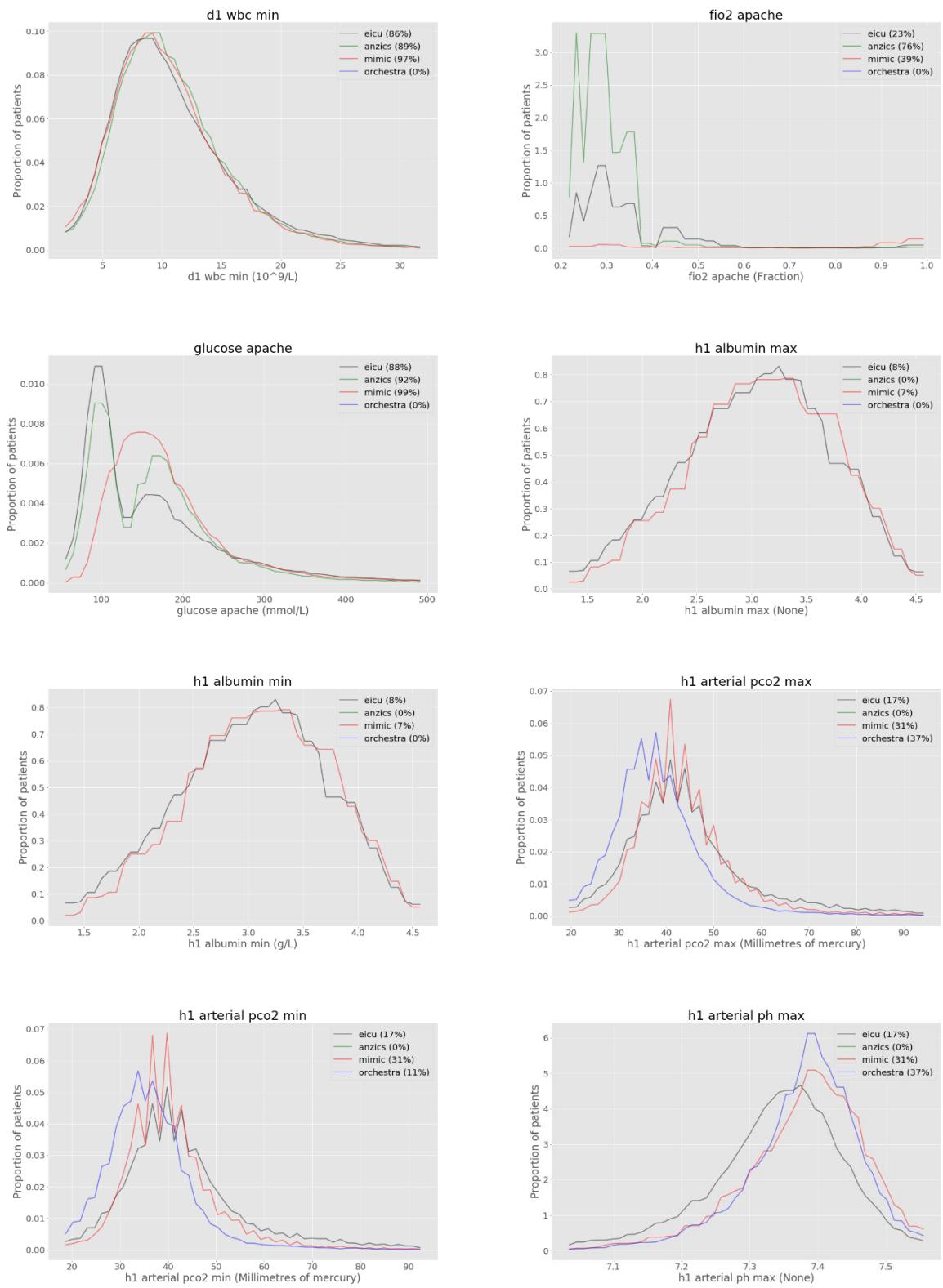


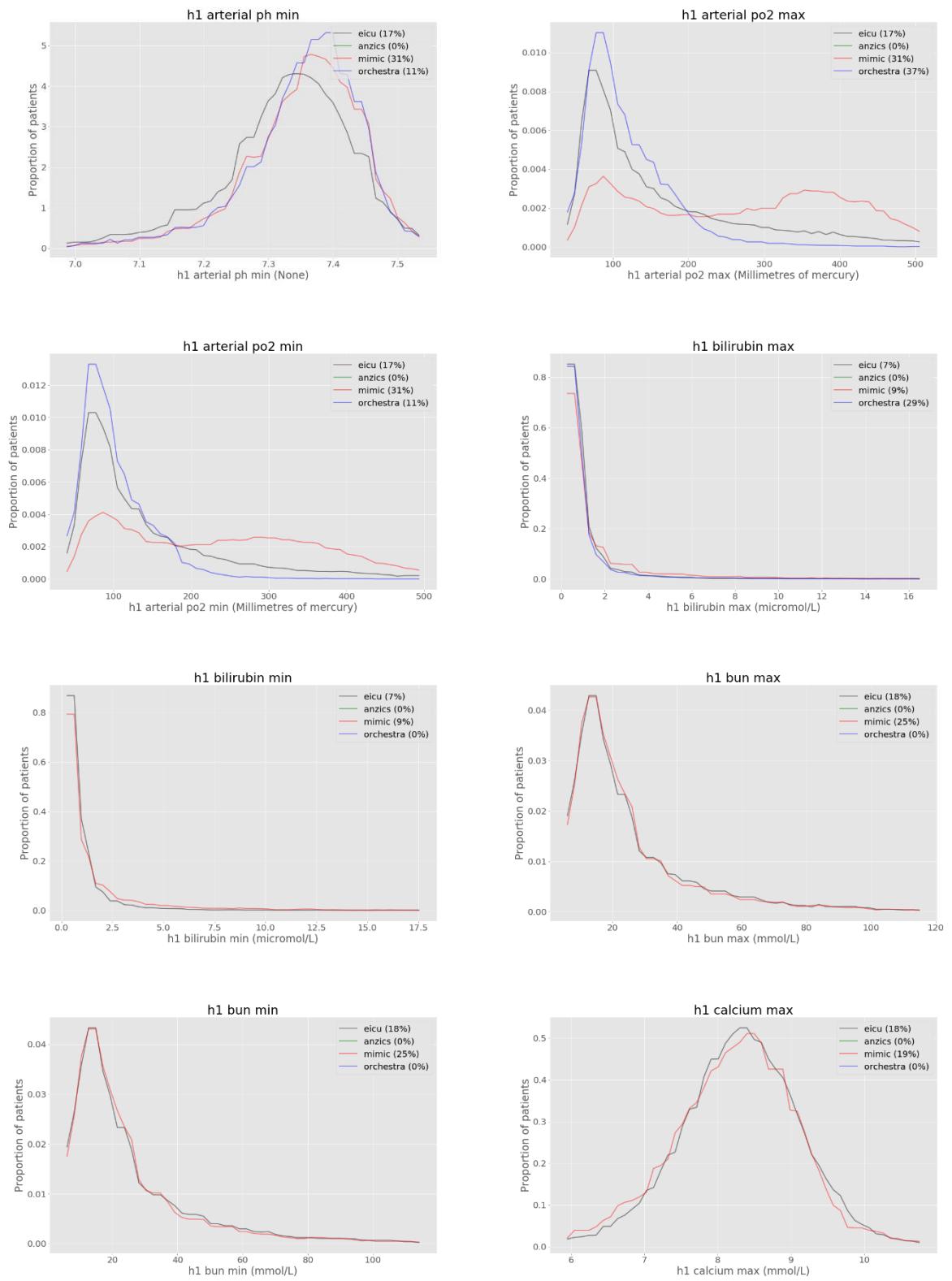


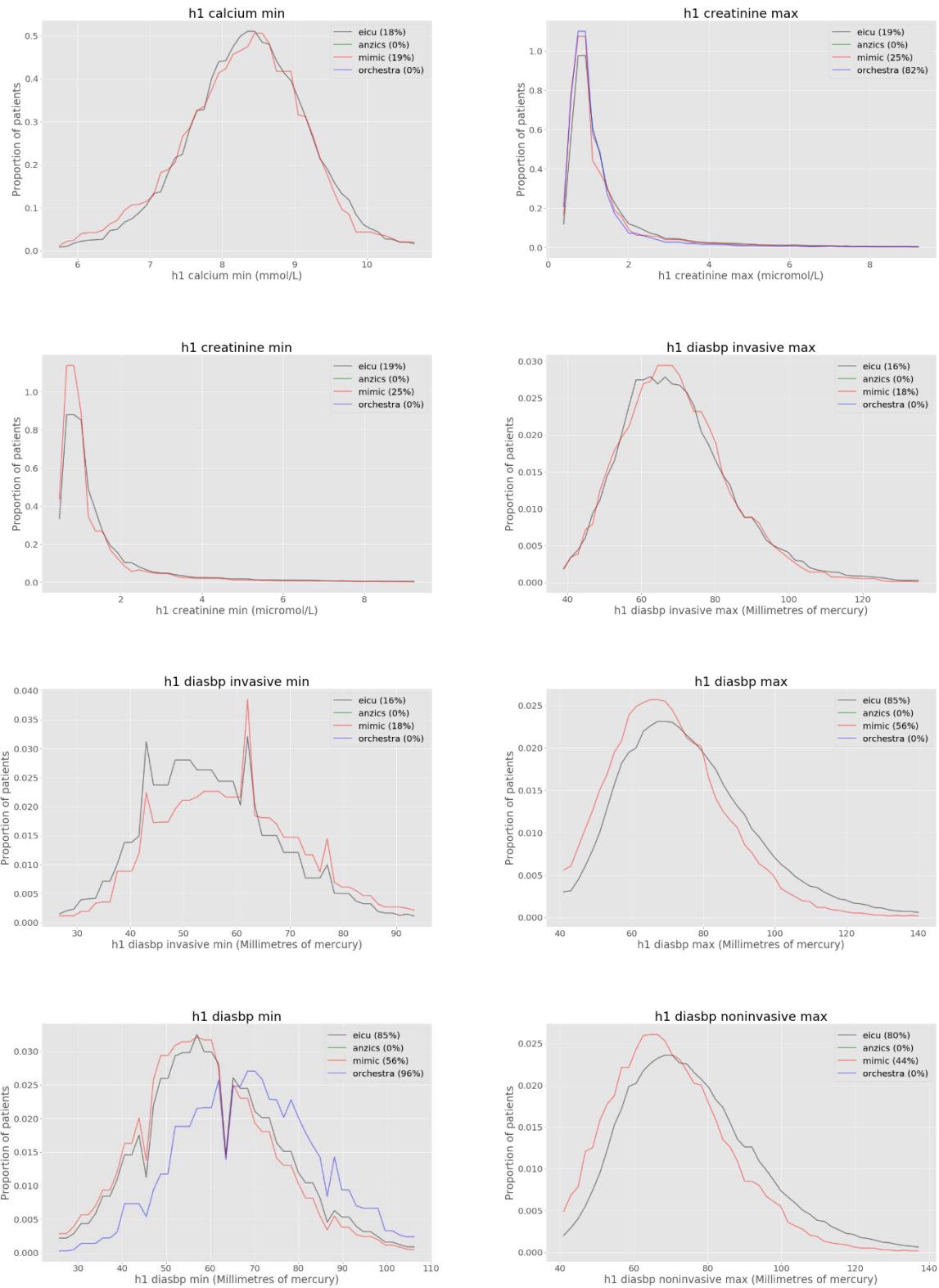


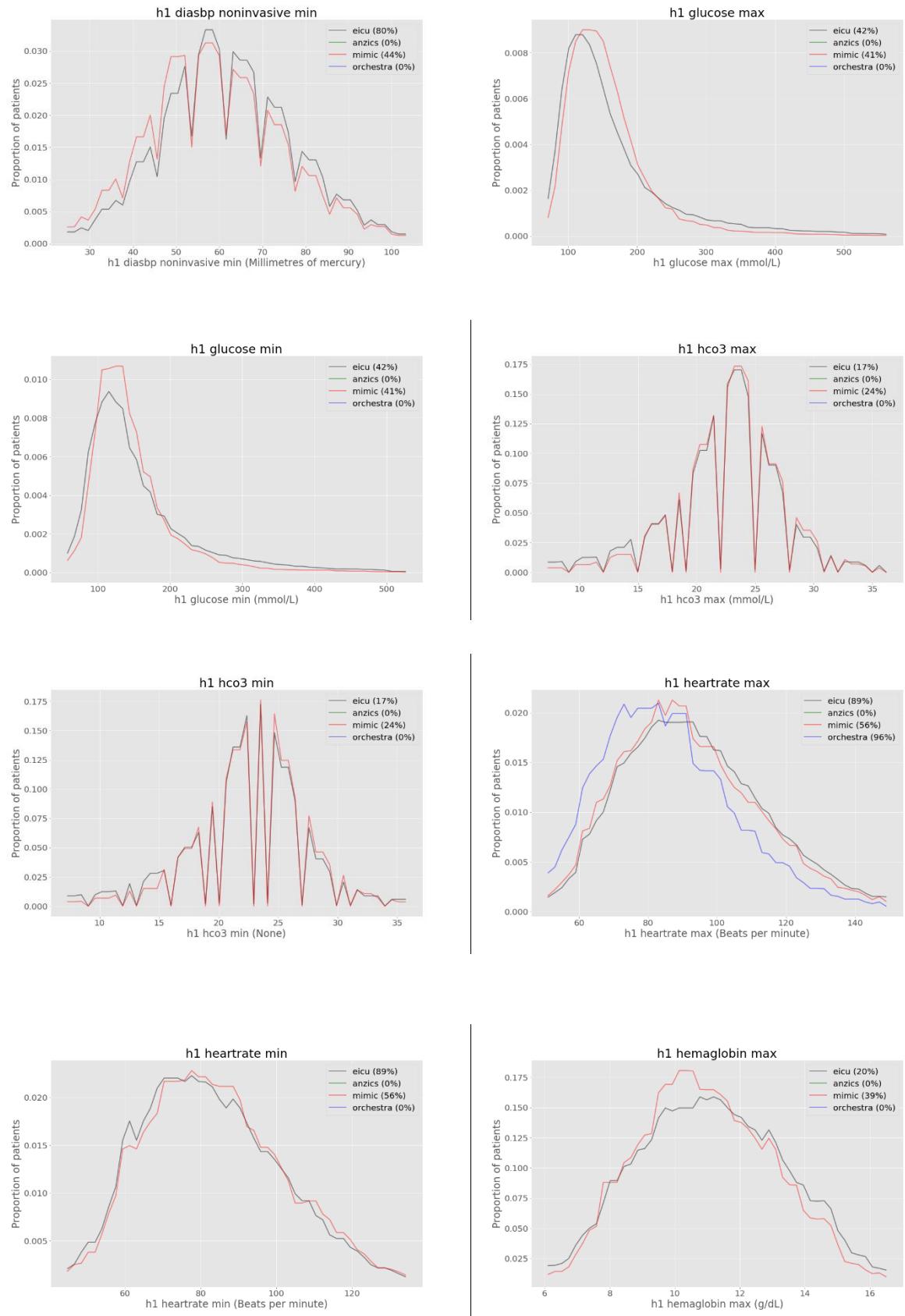


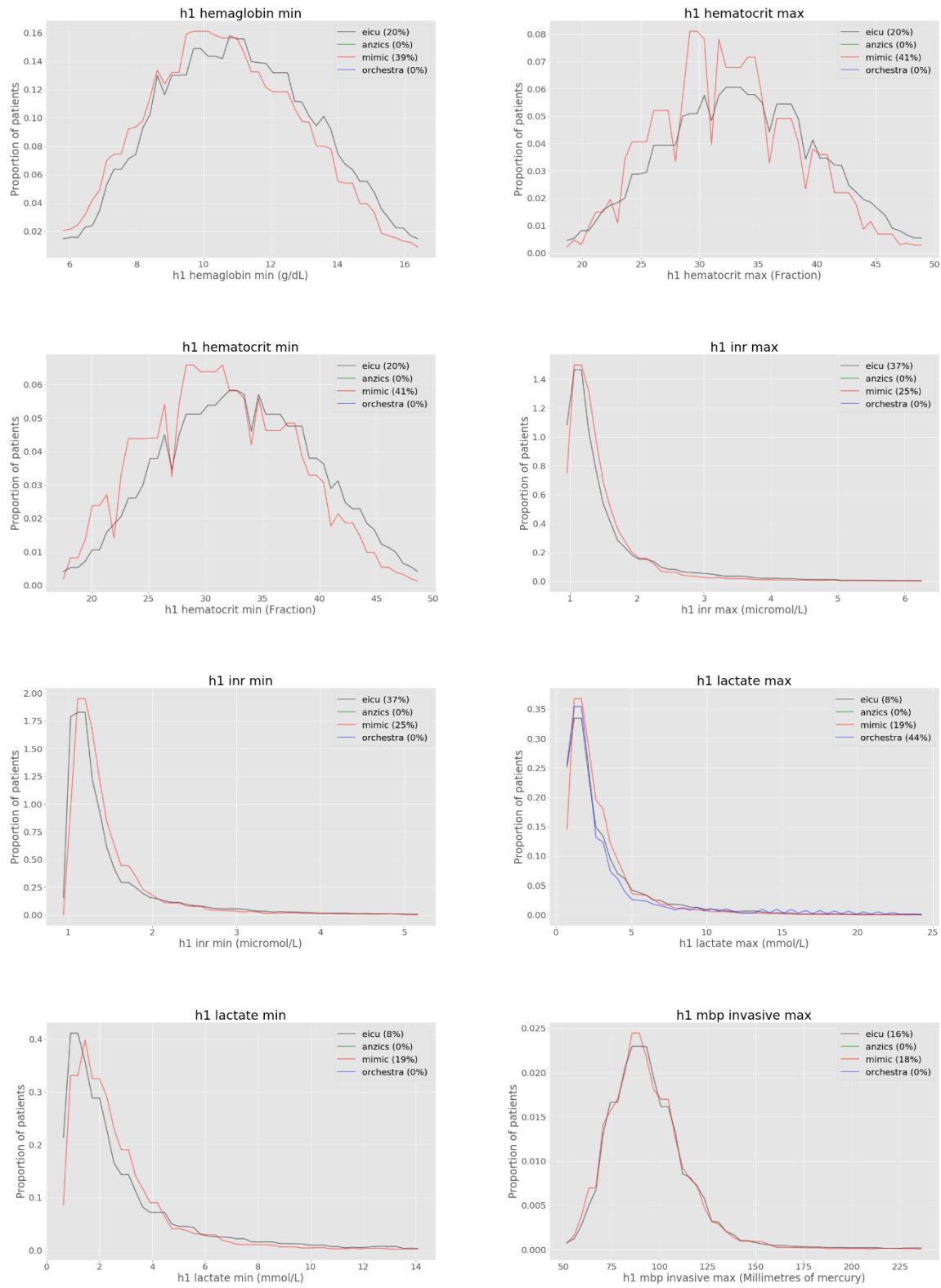


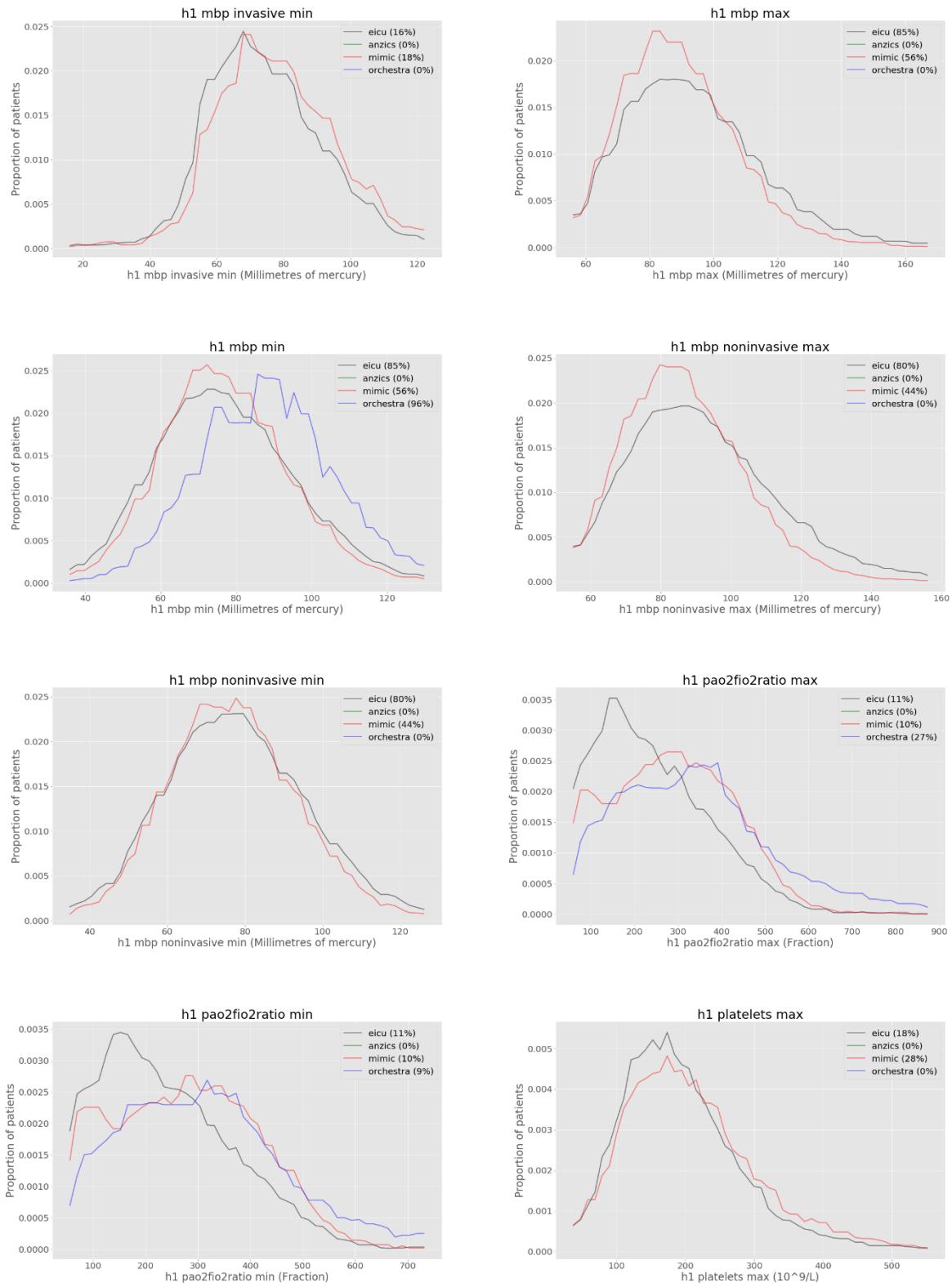


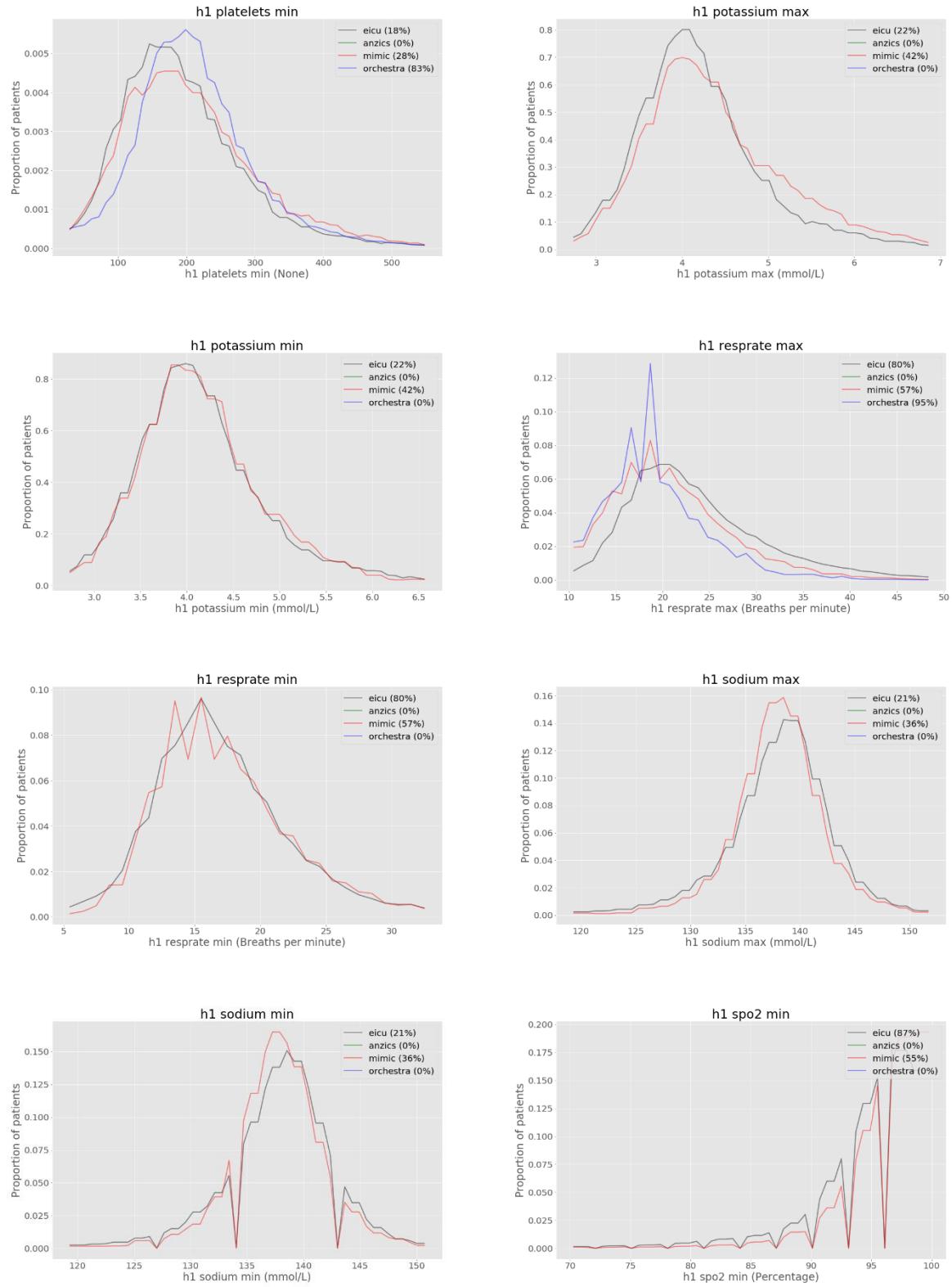


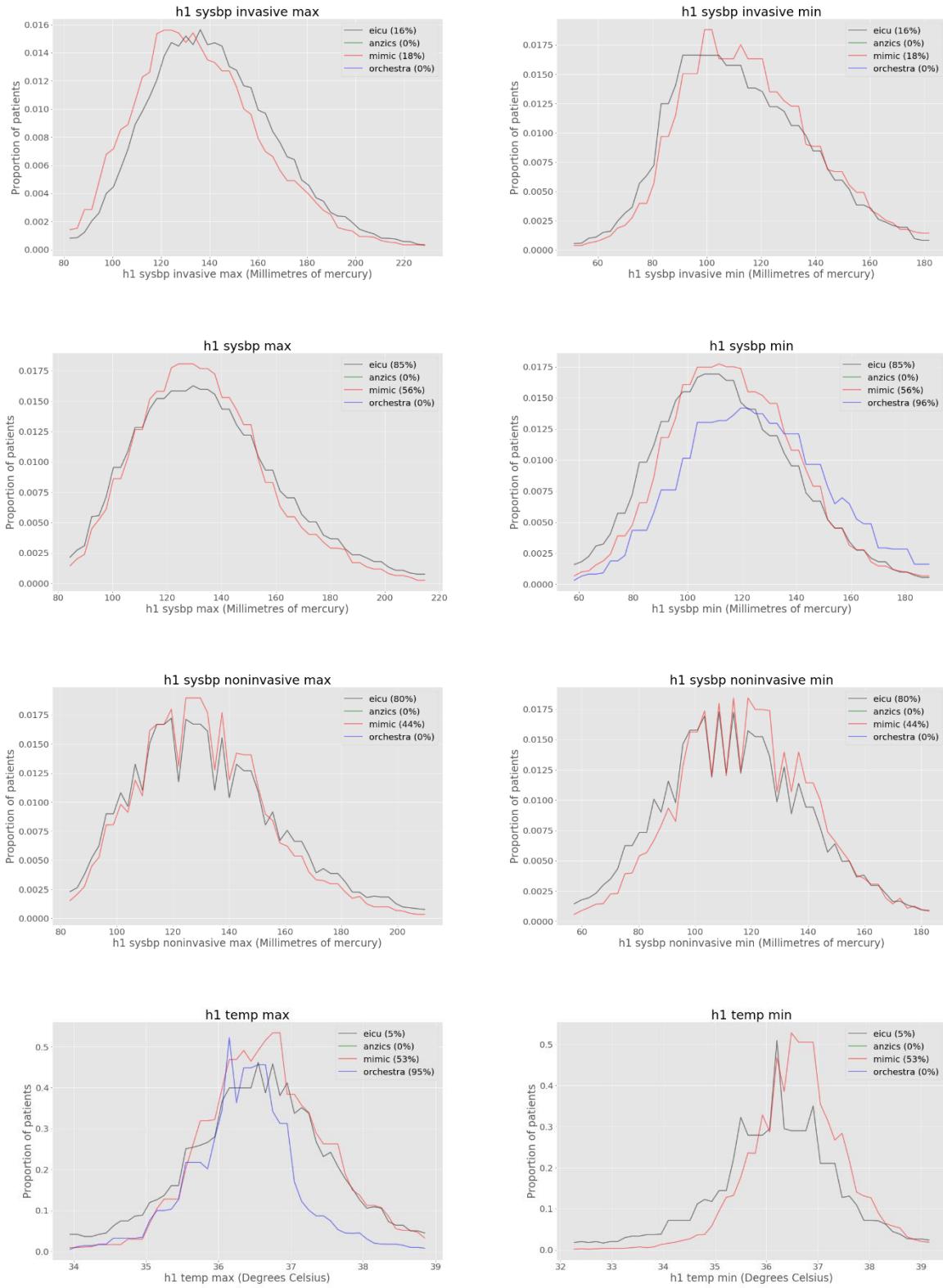


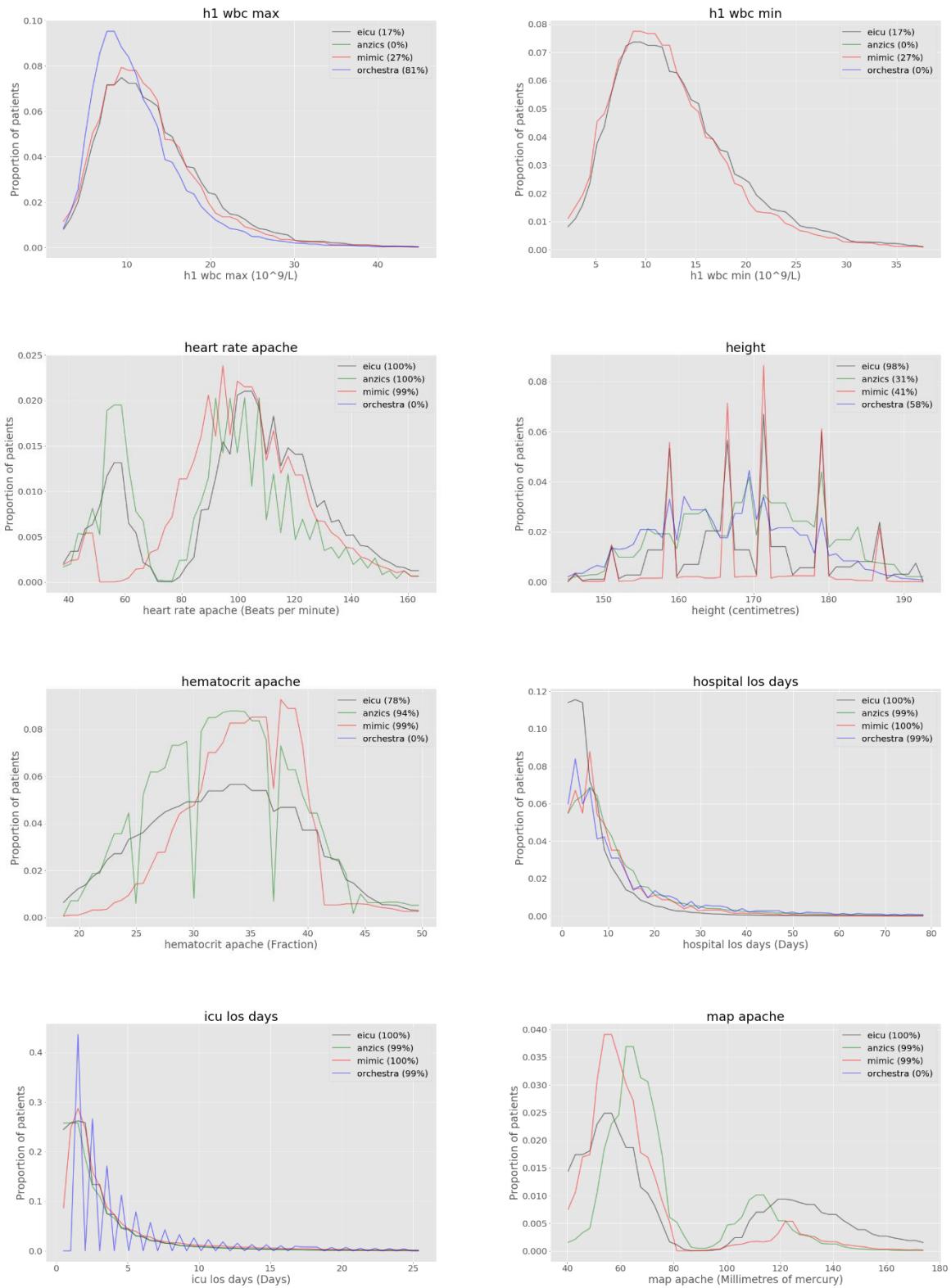


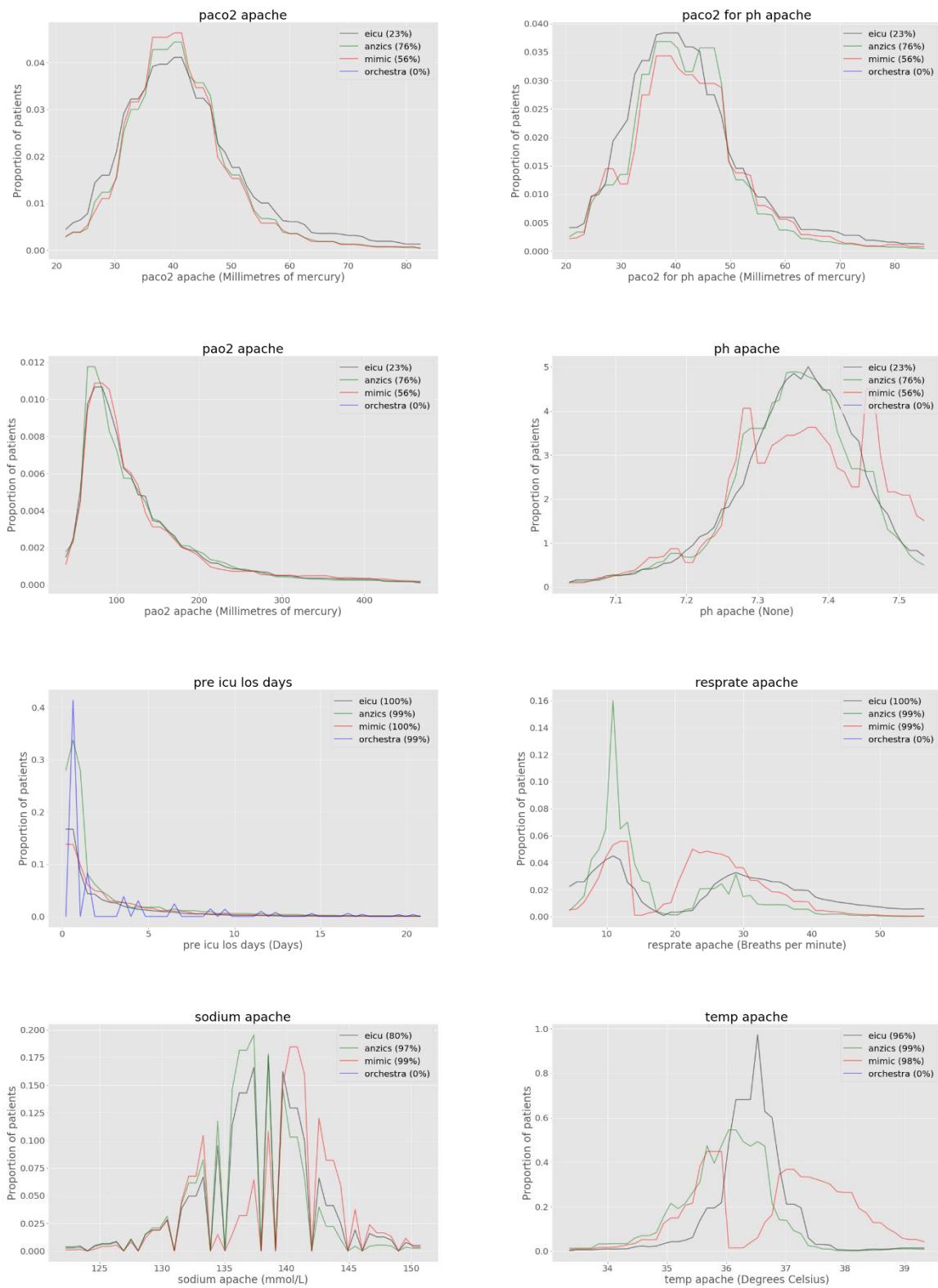


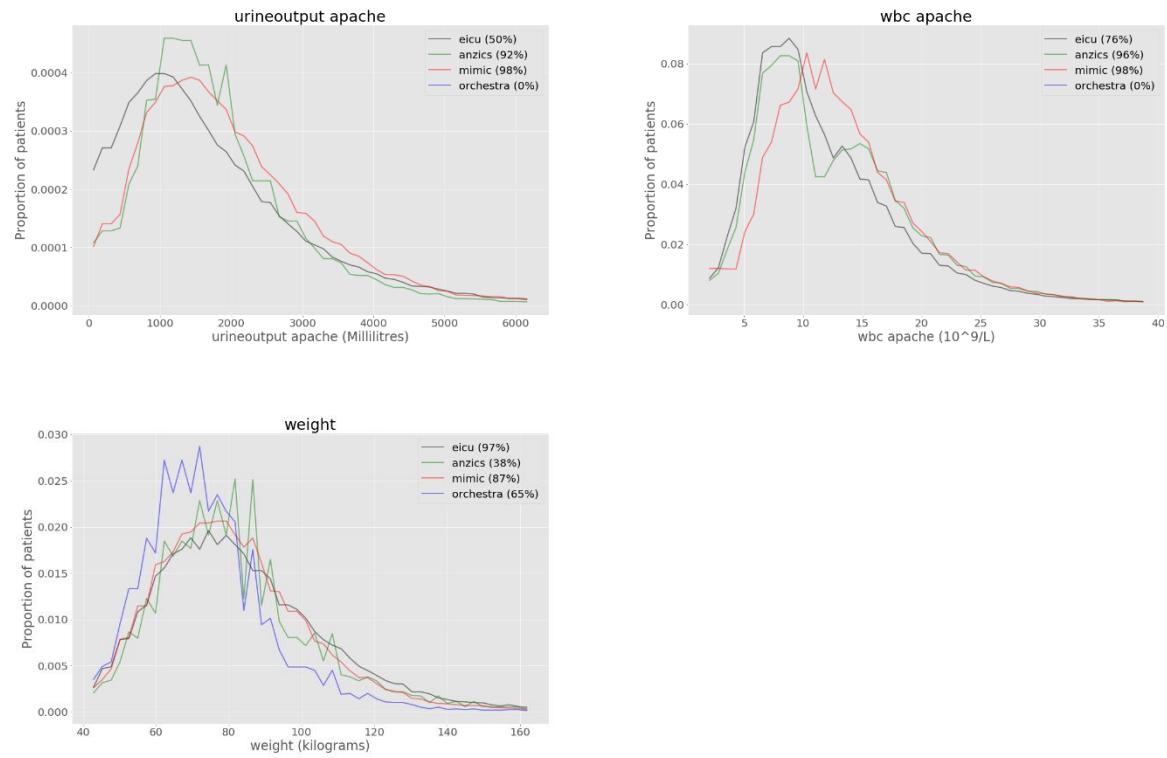












Statistics of Categorical Data

n	266136	122893	38139	3419	59693
country (n (%))					
Australia	240889 (90.51)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)
Bangladesh	0 (0.00)	0 (0.00)	0 (0.00)	(12.43) 2149	0 (0.00)
India	0 (0.00)	0 (0.00)	0 (0.00)	(62.85) 262	0 (0.00)
Nepal	0 (0.00) 25247	0 (0.00)	0 (0.00)	(7.66)	0 (0.00)
New Zealand	(9.49)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00) 583
Sri Lanka	0 (0.00)	0 (0.00)	0 (0.00)	(17.05)	0 (0.00)
USA	0 (0.00)	(100.00)	(100.00)	0 (0.00)	0 (0.00) 59693
brazil	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	(100.00)
elective_surgery (n (%))					
0	147616 (55.56)	100757 (81.99)	32099 (84.16)	0 (nan)	43041 (72.10)
1	118084	22136	6040		16652
	(44.44)	(18.01)	(15.84)	0 (nan)	(27.90)

ethnicity (n (%))					
African American	0 (0.00)	14886 (12.26)	2920 (7.66)	0 (nan)	0 (nan)
		1564	902		
Asian	0 (0.00)	94171 (1.29)	27218 (2.37)	0 (nan)	0 (nan)
		4383	1289		
Caucasian	0 (0.00)	4383 (77.58)	1289 (71.37)	0 (nan)	0 (nan)
		17611			
Hispanic	0 (0.00)	17611 (3.61)	(3.38)	0 (nan)	0 (nan)
Indigenous Native American	(100.00)	0 (0.00)	0 (0.00)	0 (nan)	0 (nan)
		935	20		
Other/Unknown	0 (0.00)	5453 (0.77)	(0.05)	0 (nan)	0 (nan)
		152596	5790		
gender (n (%))					
F		113519 (42.66)	56478 (45.97)	16554 (43.40)	1190 (35.12)
		152596	66383	21585	2198
M		(57.34)	(54.03)	(56.60)	(64.88)
hospital_death (n (%))					
0		244076 (91.82)	112084 (91.20)	33938 (88.99)	51112 (85.62)
		21731	10809	4201	8581
1		(8.18)	(8.80)	(11.01)	0 (nan) (14.38)
icu_death (n (%))					
0		251602 (94.75)	116019 (94.41)	35174 (92.23)	2472 (72.30)
		13945	6874	2965	947
1		(5.25)	(5.59)	(7.77)	(27.70) (9.59)
pregnant (n (%))					
0		38393 (98.20)	0 (nan)	1929 (98.77)	0 (nan) 0 (nan)
		702		24	
1		(1.80)	0 (nan)	(1.23)	0 (nan) 0 (nan)
smoking_status (n (%))					
Current Smoker		18809 (23.69)	0 (nan)	18043 (47.31)	0 (nan) 0 (nan)
		31731		274	
Ex-Smoker		(39.96)	0 (nan)	(0.72)	0 (nan) 0 (nan)
		28870		10870	
Never Smoked		(36.36)	0 (nan)	(28.50)	0 (nan) 0 (nan)
				8952	
Unknown	0 (0.00)	0 (nan)	(23.47)	0 (nan)	0 (nan)
teaching_hospital (n (%))					
0		90228 (33.90)	84715 (68.93)	0 (0.00)	0 (nan) 0 (nan)

	175908	38178	38139		
1	(66.10)	(31.07)	(100.00)	0 (nan)	0 (nan)
arf_apache (n (%))					
	253476	118544			
0	(95.24)	(96.46)	0 (nan)	0 (nan)	0 (nan)
	12660	4349			
1	(4.76)	(3.54)	0 (nan)	0 (nan)	0 (nan)
gcs_eyes_apache (n (%))					
	20511	10741	6062		
1	(7.95)	(8.83)	(15.98)	0 (nan)	0 (nan)
	5970	6105	2058		
2	(2.31)	(5.02)	(5.42)	0 (nan)	0 (nan)
	29547	18446	9826		
3	(11.45)	(15.17)	(25.90)	0 (nan)	0 (nan)
	201996	86286	19995		
4	(78.29)	(70.97)	(52.70)	0 (nan)	0 (nan)
gcs_motor_apache (n (%))					
	15508	7116	3865		
1	(6.01)	(5.85)	(10.23)	0 (nan)	0 (nan)
	1189	464	186		
2	(0.46)	(0.38)	(0.49)	0 (nan)	0 (nan)
	1552	742	197		
3	(0.60)	(0.61)	(0.52)	0 (nan)	0 (nan)
	4777	6380	1903		
4	(1.85)	(5.25)	(5.04)	0 (nan)	0 (nan)
	11241	10132	4169		
5	(4.36)	(8.33)	(11.03)	0 (nan)	0 (nan)
	223780	96744	27465		
6	(86.72)	(79.57)	(72.69)	0 (nan)	0 (nan)
gcs_unable_apache (n (%))					
		121578	28904		
0	0 (nan)	(98.93)	(76.03)	0 (nan)	0 (nan)
		1315	9115		
1	0 (nan)	(1.07)	(23.97)	0 (nan)	0 (nan)
gcs_verbal_apache (n (%))					
	24248	21938	3219		
1	(9.40)	(18.04)	(8.52)	0 (nan)	0 (nan)
	6087	2679	1058		
2	(2.36)	(2.20)	(2.80)	0 (nan)	0 (nan)
	6029	4270	362		
3	(2.34)	(3.51)	(0.96)	0 (nan)	0 (nan)
	21463	15089	4341		
4	(8.32)	(12.41)	(11.49)	0 (nan)	0 (nan)
	200195	77602	28816		
5	(77.59)	(63.83)	(76.24)	0 (nan)	0 (nan)
intubated_apache (n (%))					

	174095	103736			
0	(65.42)	(84.41)	0 (nan)	0 (nan)	0 (nan)
	92040	19157			
1	(34.58)	(15.59)	0 (nan)	0 (nan)	0 (nan)
ventilated_apache (n (%))					
	169440	93261	20425	2123	50458
0	(63.67)	(75.89)	(53.55)	(75.50)	(84.77)
	96696	29632	17714	689	9064
1	(36.33)	(24.11)	(46.45)	(24.50)	(15.23)

Models Results

Train = eICU

Covariates = SetB

B-splines = True

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	122893			
Model:	Logit	Df Residuals:	122845			
Method:	MLE	Df Model:	47			
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.2533			
Time:	13:41:50	Log-Likelihood:	-27324.			
converged:	True	LL-Null:	-36595.			
		LLR p-value:	0.000			
Intercept	3.6397	std err	z	P> z	[0.025	0.975]
albumin_apache_missing[T. True]	-0.1169	0.053	-2.185	0.029	-0.222	-0.012
bilirubin_apache_missing[T.True]	0.0564	0.053	1.069	0.285	-0.047	0.16
bun_apache_missing[T.True]	-0.4429	0.172	-2.578	0.01	-0.78	-0.106
creatinine_apache_missing [T.True]	0.8569	0.14	6.109	0	0.582	1.132
fio2_apache_missing[T.True]	-0.1133	0.03	-3.791	0	-0.172	-0.055
gcs_eyes_apache_missing[T. True]	1.0087	0.081	12.479	0	0.85	1.167
glucose_apache_missing[T. True]	0.1193	0.053	2.23	0.026	0.014	0.224
hematocrit_apache_missing [T.True]	0.0244	0.078	0.314	0.754	-0.128	0.177
sodium_apache_missing[T.T rue]	-0.2242	0.114	-1.971	0.049	-0.447	-0.001
temp_apache_missing[T.True]	0.6681	0.056	11.865	0	0.558	0.778
urineoutput_apache_missin g[T.True]	0.0727	0.024	3.013	0.003	0.025	0.12
wbc_apache_missing[T.True]	0.2484	0.077	3.214	0.001	0.097	0.4
albumin_apache	-0.4346	0.027	16.228	0	-0.487	-0.382
bilirubin_apache	0.0871	0.006	15.659	0	0.076	0.098
bun_apache	0.0164	0.001	25.734	0	0.015	0.018
creatinine_apache	-0.0529	0.009	-5.931	0	-0.07	-0.035
fio2_apache	1.2796	0.077	16.649	0	1.129	1.43
gcs_eyes_apache	-0.1801	0.019	-9.245	0	-0.218	-0.142
gcs_motor_apache	-0.1674	0.011	14.816	0	-0.19	-0.145
gcs_verbal_apache	-0.0695	0.011	-6.121	0	-0.092	-0.047

bs(glucose_apache, df=3, degree=3) [0]	0.8298	0.301	2.754	0.006	0.239	1.42
bs(glucose_apache, df=3, degree=3) [1]	-1.6372	0.901	-1.818	0.069	-3.402	0.128
bs(glucose_apache, df=3, degree=3) [2]	-4.4828	1.951	-2.298	0.022	-8.306	-0.659
bs(heart_rate_apache, df=3, degree=3) [0]	-4.288	0.24	17.898	0	-4.758	-3.818
bs(heart_rate_apache, df=3, degree=3) [1]	1.8801	0.166	11.311	0	1.554	2.206
bs(heart_rate_apache, df=3, degree=3) [2]	-1.2182	0.252	-4.831	0	-1.712	-0.724
hematocrit_apache	0.0053	0.002	2.743	0.006	0.002	0.009
bs(map_apache, df=3, degree=3) [0]	-3.5105	0.129	27.152	0	-3.764	-3.257
bs(map_apache, df=3, degree=3) [1]	0.5987	0.106	5.627	0	0.39	0.807
bs(map_apache, df=3, degree=3) [2]	-0.9339	0.089	-10.45	0	-1.109	-0.759
paco2_apache	-0.01	0.002	-6.299	0	-0.013	-0.007
pao2_apache	-0.002	0	-8.965	0	-0.002	-0.002
bs(ph_apache, df=3, degree=3) [0]	-3.497	2.605	-1.342	0.18	-8.604	1.609
bs(ph_apache, df=3, degree=3) [1]	-8.9876	0.999	-8.994	0	-10.946	-7.029
bs(ph_apache, df=3, degree=3) [2]	-2.4168	1.865	-1.296	0.195	-6.073	1.239
bs(resprate_apache, df=3, degree=3) [0]	-0.0306	0.13	-0.236	0.813	-0.284	0.223
bs(resprate_apache, df=3, degree=3) [1]	1.216	0.092	13.184	0	1.035	1.397
bs(resprate_apache, df=3, degree=3) [2]	0.5137	0.075	6.839	0	0.366	0.661
sodium_apache	-0.0108	0.002	-5.287	0	-0.015	-0.007
bs(temp_apache, df=3, degree=3) [0]	14.1321	1.491	9.476	0	11.209	17.055
bs(temp_apache, df=3, degree=3) [1]	0.0024	0.777	0.003	0.998	-1.52	1.525
bs(temp_apache, df=3, degree=3) [2]	5.1304	1.011 1.31E-	5.072 -	0	3.148	7.113
urineoutput_apache	-0.0001 05	0.029	11.273	0	0	0
ventilated_apache	0.5585	0.257	19.484	0	0.502	0.615
bs(wbc_apache, df=3, degree=3) [0]	0.7687	0.257	2.987	0.003	0.264	1.273
bs(wbc_apache, df=3, degree=3) [1]	2.8068	0.805	3.486	0	1.229	4.385
bs(wbc_apache, df=3, degree=3) [2]	1.8849	0.851	2.216	0.027	0.217	3.552

Train = eICU

Covariates = SetB

B-splines = False

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	122893
Model:	Logit	Df Residuals:	122859
Method:	MLE	Df Model:	33
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.2245
Time:	21:39:55	Log-Likelihood:	-28379.
converged:	True	LL-Null:	-36595.
		LLR p-value:	0.000
Intercept	26.7485	1.428	18.728
albumin_apache_missing [T.True]	-0.1485	0.053	-2.827
bilirubin_apache_missing[T.True]	0.0538	0.052	1.038
bun_apache_missing[T.True]	-0.4982	0.168	-2.967
creatinine_apache_missing[T.True]	0.825	0.137	6.023
fio2_apache_missing[T.True]	-0.3013	0.027	-11.114
gcs_eyes_apache_missing[T.True]	1.1563	0.078	14.877
glucose_apache_missing[T.True]	0.1695	0.052	3.255
hematocrit_apache_missing[T.True]	0.0082	0.076	0.107
sodium_apache_missing[T.True]	-0.2038	0.111	-1.837
temp_apache_missing[T.True]	0.6064	0.054	11.135
urineoutput_apache_missing[T.True]	0.0737	0.024	3.109
wbc_apache_missing[T.True]	0.2488	0.076	3.288
albumin_apache	-0.5006	0.026	-19.074
bilirubin_apache	0.0849	0.006	15.391
bun_apache	0.017	0.001	27.318
creatinine_apache	-0.0446	0.009	-5.164
fio2_apache	1.5129	0.075	20.266
gcs_eyes_apache	-0.1885	0.019	-9.851
gcs_motor_apache	-0.1937	0.011	-17.691
gcs_verbal_apache	-0.0828	0.011	-7.423
glucose_apache	-0.0002	0	-1.812
heart_rate_apache	0.0075	0	19.667
hematocrit_apache	0.0023	0.002	1.229

map_apache	-0.0029	0	-10.755	0	-0.003	-0.002
paco2_apache	-0.0149	0.002	-9.67	0	-0.018	-0.012
pao2_apache	-0.0021	0	-9.874	0	-0.003	-0.002
ph_apache	-2.4347	0.184	-13.247	0	-2.795	-2.074
resprate_apache	0.0173	0.001	22.611	0	0.016	0.019
sodium_apache	-0.0112	0.002	-5.618	0	-0.015	-0.007
temp_apache	-0.2209	0.01	-22.839	0	-0.24	-0.202
urineoutput_apache	-0.0002	1.31E-05	-13.474	0	0	0
ventilated_apache	0.5763	0.028	20.529	0	0.521	0.631
wbc_apache	0.0165	0.001	13.51	0	0.014	0.019

Train = eICU

Covariates = SetA

B-splines = False

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	122893
Model:	Logit	Df Residuals:	122835
Method:	MLE	Df Model:	57
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.2074
Time:	14:09:14	Log-Likelihood:	-29006.
converged:	True	LL-Null:	-36595.
		LLR p-value:	0.000

	coef	std err	z	P> z	[0.025	0.975]
Intercept	3.3405	0.916	3.646	0	1.545	5.136
gender[T.M]	0.1569	0.027	5.839	0	0.104	0.21
age_missing[T.True]	0.7682	0.048	16.035	0	0.674	0.862
bmi_missing[T.True]	0.3842	0.153	2.519	0.012	0.085	0.683
d1_CREATININE_MAX_MISSING[T.True]	0.6916	0.119	5.788	0	0.457	0.926
d1_DIASBP_MAX_MISSING[T.True]	1.2041	1.876	0.642	0.521	-2.472	4.881
d1_GLUCOSE_MAX_MISSING[T.True]	0.0472	0.07	0.676	0.499	-0.09	0.184
d1_HCO3_MAX_MISSING[T.True]	-0.1015	0.055	-1.85	0.064	-0.209	0.006
d1_HEARTRATE_MAX_MISSING[T.True]	0.2785	0.454	0.613	0.54	-0.612	1.169
d1_HEMOGLOBIN_MAX_MISSING[T.True]	-0.3627	0.135	-2.679	0.007	-0.628	-0.097
d1_HEMATOCRIT_MAX_MISSING[T.True]	0.396	0.148	2.666	0.008	0.105	0.687
d1_MBP_MAX_MISSING[T.True]	-1.0262	1.41	-0.728	0.467	-3.789	1.737
d1_PLATELETS_MAX_MISSING[T.True]	0.1041	0.109	0.958	0.338	-0.109	0.317
d1_POTASSIUM_MAX_MISSING[T.True]	0.3987	0.121	3.282	0.001	0.161	0.637

d1_resprate_max_missing[T.True]	-0.079	0.044	-1.791	0.073	-0.165	0.007
d1_sodium_max_missing[T.True]	-0.7485	0.153	-4.904	0	-1.048	-0.449
d1_sysbp_max_missing[T.True]	0.21	1.318	0.159	0.873	-2.372	2.792
d1_temp_max_missing[T.True]	-0.6748	0.035	-19.213	0	-0.744	-0.606
d1_wbc_max_missing[T.True]	-0.1047	0.125	-0.835	0.404	-0.35	0.141
gender_missing[T.True]	0.1793	0.549	0.327	0.744	-0.897	1.255
height_missing[T.True]	0.4447	0.136	3.262	0.001	0.177	0.712
weight_missing[T.True]	-0.3259	0.143	-2.271	0.023	-0.607	-0.045
age	0.0269	0.001	32.535	0	0.025	0.029
bmi	0.0009	0.002	0.574	0.566	-0.002	0.004
d1_creatinine_max	-0.1433	0.026	-5.467	0	-0.195	-0.092
d1_creatinine_min	0.2231	0.029	7.715	0	0.166	0.28
d1_diasbp_max	-0.0043	0.001	-7.65	0	-0.005	-0.003
d1_diasbp_min	-0.0015	0.002	-0.97	0.332	-0.005	0.002
d1_glucose_max	-0.0001	0	-1.049	0.294	0	0
d1_glucose_min	0.0026	0	9.575	0	0.002	0.003
d1_hco3_max	-0.0179	0.006	-3.127	0.002	-0.029	-0.007
d1_hco3_min	-0.0321	0.005	-5.884	0	-0.043	-0.021
d1_heartrate_max	0.0159	0.001	30.668	0	0.015	0.017
d1_heartrate_min	-0.0091	0.001	-12.627	0	-0.011	-0.008
d1_hemoglobin_max	-0.1201	0.026	-4.575	0	-0.171	-0.069
d1_hemoglobin_min	-0.1961	0.028	-7.026	0	-0.251	-0.141
d1_hematocrit_max	0.0385	0.009	4.144	0	0.02	0.057
d1_hematocrit_min	0.0671	0.01	7.003	0	0.048	0.086
d1_mbp_max	0.0014	0	3.304	0.001	0.001	0.002
d1_mbp_min	-0.0177	0.001	-12.149	0	-0.021	-0.015
d1_platelets_max	0.0037	0	7.822	0	0.003	0.005
d1_platelets_min	-0.0055	0.001	-10.92	0	-0.006	-0.005
d1_potassium_max	0.1792	0.025	7.307	0	0.131	0.227
d1_potassium_min	-0.0782	0.028	-2.773	0.006	-0.133	-0.023
d1_resprate_max	0.0086	0.001	7.795	0	0.006	0.011
d1_resprate_min	0.0203	0.002	8.644	0	0.016	0.025
d1_sodium_max	0.0636	0.005	13.199	0	0.054	0.073
d1_sodium_min	-0.0542	0.005	-11.219	0	-0.064	-0.045
d1_sysbp_max	0.0036	0	7.461	0	0.003	0.004
d1_sysbp_min	-0.0139	0.001	-16.05	0	-0.016	-0.012
d1_temp_max	-0.1752	0.023	-7.747	0	-0.219	-0.131
d1_temp_min	-0.0303	0.007	-4.584	0	-0.043	-0.017
d1_wbc_max	-0.0004	0.002	-0.195	0.845	-0.004	0.004
d1_wbc_min	0.0184	0.003	7.117	0	0.013	0.024

elective_surgery	-1.4651	0.045	-32.859	0	-1.552	-1.378
height	0.0003	0.001	0.293	0.769	-0.002	0.002
pre_icu_los_days	0.0515	0.003	14.91	0	0.045	0.058
weight	-0.0026	0.001	-3.453	0.001	-0.004	-0.001

Train = eICU

Covariates = SetC

B-splines = False

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	122893
Model:	Logit	Df Residuals:	122848
Method:	MLE	Df Model:	44
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.1436
Time:	14:38:35	Log-Likelihood:	-31339.
converged:	True	LL-Null:	-36595.
		LLR p-value:	0.000

	coef	std err	z	P> z	[0.025	0.975]
Intercept	25.6848	1.714	14.981	0	22.324	29.045
gender[T.M]	0.0942	0.026	3.682	0	0.044	0.144
age_missing[T.True]	0.8586	0.046	18.773	0	0.769	0.948
bmi_missing[T.True]	0.4005	0.144	2.778	0.005	0.118	0.683
gender_missing[T.True]	0.3603	0.495	0.728	0.467	-0.61	1.331
h1_arterial_pco2_max_missing[T.True]	-0.4512	0.194	-2.329	0.02	-0.831	-0.072
h1_arterial_ph_max_missing[T.True]	0.0253	0.119	0.212	0.832	-0.208	0.259
h1_arterial_po2_max_missing[T.True]	-0.1459	0.196	-0.746	0.456	-0.529	0.238
h1_bilirubin_max_missing[T.True]	-0.2185	0.046	-4.731	0	-0.309	-0.128
h1_creatinine_max_missing[T.True]	0.0457	0.044	1.032	0.302	-0.041	0.133
h1_heartrate_max_missing[T.True]	0.5432	0.075	7.256	0	0.396	0.69
h1_lactate_max_missing[T.True]	-0.2732	0.036	-7.661	0	-0.343	-0.203
h1_mbp_min_missing[T.True]	-1.1688	0.353	-3.313	0.001	-1.86	-0.477
h1_pao2fio2ratio_min_missing[T.True]	-0.0396	0.047	-0.845	0.398	-0.132	0.052
h1_platelets_min_missing[T.True]	0.0456	0.123	0.37	0.712	-0.196	0.287
h1_resprate_max_missing[T.True]	-0.011	0.04	-0.273	0.785	-0.09	0.068
h1_sysbp_min_missing[T.True]	0.925	0.348	2.657	0.008	0.243	1.607
h1_temp_max_missing[T.True]	-0.641	0.045	-14.323	0	-0.729	-0.553
h1_wbc_max_missing[T.True]	-0.0243	0.125	-0.195	0.846	-0.269	0.22

height_missing[T.True]	0.496	0.129	3.855	0	0.244	0.748
weight_missing[T.True]	-0.382	0.135	-2.835	0.005	-0.646	-0.118
age	0.03	0.001	38.07	0	0.028	0.032
bmi	0.0006	0.002	0.345	0.73	-0.003	0.004
elective_surgery	-1.5149	0.046	-32.707	0	-1.606	-1.424
h1_arterial_pco2_max	-0.0014	0.007	-0.193	0.847	-0.015	0.013
h1_arterial_pco2_min	-0.0059	0.007	-0.797	0.425	-0.02	0.009
h1_arterial_ph_max	-1.2584	1.023	-1.23	0.219	-3.264	0.747
h1_arterial_ph_min	-1.3455	1.011	-1.33	0.183	-3.328	0.637
h1_arterial_po2_max	-0.002	0.001	-3.228	0.001	-0.003	-0.001
h1_arterial_po2_min	0.004	0.001	5.964	0	0.003	0.005
h1_bilirubin_max	0.1062	0.011	9.738	0	0.085	0.128
h1_creatinine_max	0.0434	0.012	3.736	0	0.021	0.066
h1_diasbp_min	0.0045	0.002	2.498	0.013	0.001	0.008
h1_heartrate_max	0.0115	0.001	21.818	0	0.01	0.013
h1_lactate_max	0.1733	0.009	19.111	0	0.156	0.191
h1_mbp_min	-0.0188	0.002	-9.633	0	-0.023	-0.015
h1_pao2fio2ratio_min	-0.0019	0	-7.586	0	-0.002	-0.001
h1_platelets_min	-0.0008	0	-3.36	0.001	-0.001	0
h1_resprate_max	0.0215	0.001	14.881	0	0.019	0.024
h1_sysbp_min	-0.0061	0.001	-7.235	0	-0.008	-0.004
h1_temp_max	-0.2541	0.024	-10.402	0	-0.302	-0.206
h1_wbc_max	0.009	0.002	4.819	0	0.005	0.013
height	-0.0003	0.001	-0.287	0.774	-0.002	0.002
pre_icu_los_days	0.0441	0.003	13.228	0	0.038	0.051
weight	-0.0018	0.001	-2.512	0.012	-0.003	0

Train = ANZICS

Covariates = SetB

B-splines = False

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	265807
Model:	Logit	Df Residuals:	265764
Method:	MLE	Df Model:	42
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.2618
Time:	21:37:05	Log-Likelihood:	-55537.
converged:	True	LL-Null:	-75233.
		LLR p-value:	0.000

	coef	std err	z	P> z	[0.025	0.975]
Intercept	16.11	0.703	22.909	0	14.732	17.488
albumin_apache_missing[T.True]	0.0548	0.061	0.901	0.368	-0.064	0.174
bilirubin_apache_missing[T.True]	-0.1399	0.044	-3.205	0.001	-0.225	-0.054

bun_apache_missing[T.True]	-0.0531	0.104	-0.511	0.609	-0.257	0.151
creatinine_apache_missing[T.True]	0.6339	0.137	4.642	0	0.366	0.902
fio2_apache_missing[T.True]	0.3225	0.308	1.047	0.295	-0.282	0.927
gcs_eyes_apache_missing[T.True]	-0.0823	0.73	-0.113	0.91	-1.514	1.349
gcs_motor_apache_missing[T.True]	-0.2958	0.841	-0.352	0.725	-1.943	1.352
gcs_verbal_apache_missing[T.True]	0.8738	0.526	1.662	0.096	-0.156	1.904
glucose_apache_missing[T.True]	-0.0053	0.04	-0.132	0.895	-0.084	0.074
hematocrit_apache_missing[T.True]	-0.2134	0.065	-3.298	0.001	-0.34	-0.087
map_apache_missing[T.True]	0.7676	0.196	3.925	0	0.384	1.151
paco2_apache_missing[T.True]	-0.7311	0.471	-1.552	0.121	-1.655	0.192
paco2_for_ph_apache_missing[T.True]	0.0674	0.316	0.213	0.831	-0.552	0.687
pao2_apache_missing[T.True]	-0.4555	0.421	-1.082	0.279	-1.28	0.37
ph_apache_missing[T.True]	0.6969	0.316	2.205	0.027	0.078	1.316
resprate_apache_missing[T.True]	0.2696	0.119	2.266	0.023	0.036	0.503
sodium_apache_missing[T.True]	-0.1765	0.107	-1.647	0.1	-0.387	0.034
temp_apache_missing[T.True]	1.5473	0.101	15.252	0	1.348	1.746
urineoutput_apache_missing[T.True]	0.0948	0.035	2.721	0.007	0.027	0.163
wbc_apache_missing[T.True]	0.3922	0.101	3.898	0	0.195	0.589
albumin_apache	-0.464	0.014	-32.682	0	-0.492	-0.436
bilirubin_apache	0.0927	0.003	26.716	0	0.086	0.1
bun_apache	0.0146	0	43.572	0	0.014	0.015
creatinine_apache	-0.0269	0.005	-4.953	0	-0.038	-0.016
fio2_apache	1.1597	0.045	25.799	0	1.072	1.248
gcs_eyes_apache	-0.1363	0.016	-8.489	0	-0.168	-0.105
gcs_motor_apache	-0.1534	0.009	-16.47	0	-0.172	-0.135
gcs_verbal_apache	-0.2953	0.01	-28.256	0	-0.316	-0.275
glucose_apache	9.79E-06	8.10E-05	0.862	0.389	8.90E-06	0
heart_rate_apache	0.0094	0	33.812	0	0.009	0.01
hematocrit_apache	-0.0024	0.001	-1.818	0.069	-0.005	0
map_apache	-0.0033	0	-9.488	0	-0.004	-0.003
paco2_apache	0.0063	0.001	5.071	0	0.004	0.009
paco2_for_ph_apache	-0.0054	0.001	-4.436	0	-0.008	-0.003
pao2_apache	-0.0026	0	-21.262	0	-0.003	-0.002

ph_apache	-1.2523	0.089	-14.126	0	-1.426	-1.079
resprate_apache	0.0443	0.001	58.003	0	0.043	0.046
sodium_apache	-0.003	0.002	-1.956	0.05	-0.006	6.19E-06
temp_apache	-0.196	0.008	-26.108	0	-0.211	-0.181
urineoutput_apache	-0.0003	1.90E-07	-37.468	0	0	0
ventilated_apache	0.1332	0.022	5.937	0	0.089	0.177
wbc_apache	0.0061	0.001	9.623	0	0.005	0.007

Train = ANZICS

Covariates = SetB

B-splines = True

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	265807
Model:	Logit	Df Residuals:	265750
Method:	MLE	Df Model:	56
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.2829
Time:	13:45:26	Log-Likelihood:	-53946.
converged:	True	LL-Null:	-75233.
		LLR p-value:	0.000

	coef	std err	z	P> z	[0.025	0.975]
Intercept	7.2335	0.651	11.103	0	5.957	8.51
albumin_apache_missing[T.True]	0.0541	0.062	0.875	0.382	-0.067	0.175
bilirubin_apache_missing[T.True]	-0.14	0.044	-3.154	0.002	-0.227	-0.053
bun_apache_missing[T.True]	-0.0966	0.106	-0.912	0.362	-0.304	0.111
creatinine_apache_missing[T.True]	0.6597	0.14	4.728	0	0.386	0.933
fio2_apache_missing[T.True]	0.3776	0.313	1.206	0.228	-0.236	0.991
gcs_eyes_apache_missing[T.True]	-0.74	0.827	-0.895	0.371	-2.36	0.88
gcs_motor_apache_missing[T.True]	0.2339	0.921	0.254	0.799	-1.57	2.038
gcs_verbal_apache_missing[T.True]	0.9881	0.522	1.892	0.058	-0.035	2.011
glucose_apache_missing[T.True]	-0.0135	0.041	-0.327	0.744	-0.095	0.068
hematocrit_apache_missing[T.True]	-0.2127	0.066	-3.234	0.001	-0.342	-0.084
map_apache_missing[T.True]	1.0252	0.199	5.162	0	0.636	1.415
paco2_apache_missing[T.True]	-0.7537	0.473	-1.594	0.111	-1.681	0.173
paco2_for_ph_apache_missing[T.True]	0.0699	0.326	0.214	0.831	-0.57	0.71
pao2_apache_missing[T.True]	-0.3467	0.416	-0.833	0.405	-1.163	0.469

ph_apache_missing[T.T rue]	0.6548	0.326	2.007	0.045	0.015	1.294
resprate_apache_mis sing[T.True]	0.2652	0.123	2.162	0.031	0.025	0.506
sodium_apache_mis sing[T.True]	-0.1522	0.111	-1.372	0.17	-0.37	0.065
temp_apache_mis sing[T.True]	1.4658	0.105	13.957	0	1.26	1.672
urineoutput_apache_mi ssing[T.True]	0.0791	0.036	2.216	0.027	0.009	0.149
wbc_apache_missing[T. True]	0.3685	0.103	3.581	0	0.167	0.57
albumin_apache	-0.4471	0.014	-30.896	0	-0.475	-0.419
bilirubin_apache	0.0911	0.003	26.33	0	0.084	0.098
bun_apache	0.0148	0	43.781	0	0.014	0.015
creatinine_apache	-0.0419	0.006	-7.538	0	-0.053	-0.031
fio2_apache	0.9827	0.046	21.35	0	0.892	1.073
gcs_eyes_apache	-0.1325	0.016	-8.119	0	-0.164	-0.101
gcs_motor_apache	-0.1359	0.009	-14.312	0	-0.155	-0.117
gcs_verbal_apache	-0.2891	0.011	-27.161	0	-0.31	-0.268
bs(glucose_apache, df=3, degree=3) [0]	8.45E-01	2.28E-01	3.702	0	0.01	1.292
bs(glucose_apache, df=3, degree=3) [1]	-0.1674	0.681	-0.246	0.806	-1.502	1.167
bs(glucose_apache, df=3, degree=3) [2]	-5.4603	1.512	-3.611	0	-8.424	-2.497
bs(heart_rate_apache, df=3, degree=3) [0]	-6.5774	0.366	-17.966	0	-7.295	-5.86
bs(heart_rate_apache, df=3, degree=3) [1]	6.7615	0.375	18.024	0	6.026	7.497
bs(heart_rate_apache, df=3, degree=3) [2]	-7.7654	0.815	-9.53	0	-9.362	-6.168
hematocrit_apache	-0.002	0.001	-1.507	0.132	-0.005	0.001
bs(map_apache, df=3, degree=3) [0]	-10.8646	0.384	-28.275	0	11.618	-10.112
bs(map_apache, df=3, degree=3) [1]	0.7093	0.305	2.325	0.02	0.111	1.307
bs(map_apache, df=3, degree=3) [2]	-5.431	0.676	-8.035	0	-6.756	4.11E+0
paco2_apache	0.0052	0.001	4.144	0	0.003	0.008
paco2_for_ph_apache	-0.0027	1.00E-03	-2.251	0.024	-0.005	0
pao2_apache	-0.0024	0	-19.623	0	-0.003	-0.002
bs(ph_apache, df=3, degree=3) [0]	-3.9789	0.703	-5.659	0	-5.357	-2.601
bs(ph_apache, df=3, degree=3) [1]	-4.0564	0.353	-11.498	0	-4.748	-3.365
bs(ph_apache, df=3, degree=3) [2]	2.1687	0.833	2.603	0.009	0.536	3.802
bs(resprate_apache, df=3, degree=3) [0]	-0.1043	0.214	-0.487	0.627	-0.524	0.316
bs(resprate_apache, df=3, degree=3) [1]	4.0145	0.207	19.418	0	3.609	4.42

bs(resprate_apache,							
df=3, degree=3) [2]	-0.0879	0.361	-0.243	0.808	-0.796	0.621	
sodium_apache	-0.0014	0.002	-0.881	0.378	-0.004	0.002	
bs(temp_apache, df=3,							
degree=3) [0]	9.9003	1.038	9.537	0	7.866	11.935	
bs(temp_apache, df=3,							
degree=3) [1]	-7.8751	0.378	-20.857	0	-8.615	-7.135	
bs(temp_apache, df=3,							
degree=3) [2]	9.7933	0.956	10.246	0	7.92	11.667	
urineoutput_apache	-0.0003	8.19E-06	-35.919	0	0	0	0
ventilated_apache	0.1302	0.023	5.691	0	0.085	0.175	
bs(wbc_apache, df=3,							
degree=3) [0]	0.5017	0.172	2.919	0.004	0.165	0.839	
bs(wbc_apache, df=3,							
degree=3) [1]	2.4589	0.594	4.14	0	1.295	3.623	
bs(wbc_apache, df=3,							
degree=3) [2]	0.0417	0.582	0.072	0.943	-1.098	1.182	

Train = ANZICS
Covariates = SetA
B-splines = False

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	265807
Model:	Logit	Df Residuals:	265735
Method:	MLE	Df Model:	71
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.2350
Time:	14:04:33	Log-Likelihood:	-57549.
converged:	True	LL-Null:	-75233.
		LLR p-value:	0.000

	coef	std err	z	P> z	[0.025	0.975]
Intercept	5.7601	0.525	10.961	0	4.73	6.79
gender[T.M]	0.1222	0.017	7.123	0	0.089	0.156
bmi_missing[T.True]	0.225	0.124	1.819	0.069	-0.017	0.467
d1_creatinine_max_missing[T.True]	0.7876	0.118	6.654	0	0.556	1.02
d1_creatinine_min_missing[T.True]	0.0051	0.078	0.065	0.948	-0.147	0.158
d1_diasbp_max_missing[T.True]	-0.2232	0.092	-2.434	0.015	-0.403	-0.043
d1_diasbp_min_missing[T.True]	0.3716	0.107	3.472	0.001	0.162	0.581
d1_glucose_max_missing[T.True]	0.0146	0.068	0.214	0.831	-0.119	0.148
d1_glucose_min_missing[T.True]	-0.3124	0.063	-4.983	0	-0.435	-0.19
d1_hco3_max_missing[T.True]	0.1592	0.096	1.66	0.097	-0.029	0.347
d1_hco3_min_missing[T.True]	-0.0623	0.095	-0.656	0.512	-0.248	0.124

d1_hemoglobin_max_missing[T.True]	-0.0713	0.121	-0.591	0.554	-0.308	0.165
d1_hemoglobin_min_missing[T.True]	0.0487	0.116	0.42	0.674	-0.178	0.276
d1_hematocrit_max_missing[T.True]	-0.2462	0.102	-2.421	0.015	-0.445	-0.047
d1_hematocrit_min_missing[T.True]	0.0033	0.1	0.033	0.974	-0.193	0.2
d1_mbp_max_missing[T.True]	0.0105	0.236	0.045	0.964	-0.452	0.473
d1_mbp_min_missing[T.True]	0.2388	0.2	1.192	0.233	-0.154	0.632
d1_platelets_max_missing[T.True]	0.0889	0.114	0.78	0.435	-0.134	0.312
d1_platelets_min_missing[T.True]	0.0481	0.109	0.44	0.66	-0.166	0.262
d1_potassium_max_missing[T.True]	0.2107	0.162	1.301	0.193	-0.107	0.528
d1_potassium_min_missing[T.True]	0.0729	0.132	0.551	0.582	-0.186	0.332
d1_resprate_max_missing[T.True]	-0.6246	0.168	-3.714	0	-0.954	-0.295
d1_resprate_min_missing[T.True]	0.9639	0.128	7.557	0	0.714	1.214
d1_sodium_max_missing[T.True]	-0.6832	0.183	-3.734	0	-1.042	-0.325
d1_sodium_min_missing[T.True]	0.0678	0.138	0.491	0.623	-0.203	0.339
d1_sysbp_max_missing[T.True]	0.5114	0.285	1.792	0.073	-0.048	1.071
d1_sysbp_min_missing[T.True]	0.2886	0.251	1.152	0.249	-0.202	0.78
d1_temp_max_missing[T.True]	1.1934	0.132	9.069	0	0.936	1.451
d1_temp_min_missing[T.True]	0.6926	0.113	6.107	0	0.47	0.915
d1_wbc_max_missing[T.True]	4.49E-01	1.05E-01	4.29	0	2.44E-01	0.654
d1_wbc_min_missing[T.True]	-0.1741	0.067	-2.597	0.009	-0.306	-0.043
elective_surgery_missing[T.True]	-0.339	0.191	-1.773	0.076	-0.714	0.036
gender_missing[T.True]	0.3272	0.794	0.412	0.68	-1.229	1.883
height_missing[T.True]	-0.0645	0.12	-0.538	0.59	-0.299	0.17
pre_icu_los_days_missing[T.True]	0.2178	0.096	2.274	0.023	0.03	0.405
weight_missing[T.True]	-0.0367	0.029	-1.275	0.202	-0.093	0.02
age	0.0324	0.001	61.238	0	0.031	0.033
bmi	-0.0001	0	-0.455	0.649	-0.001	0
d1_creatinine_max	-0.0508	0.011	-4.417	0	-0.073	-2.80E-02
d1_creatinine_min	0.124	0.014	8.575	0	0.096	0.152
d1_diasbp_max	-0.0028	1.00E-03	-2.647	0.008	-0.005	-0.001

d1_diasbp_min	0.0009	0.001	0.582	0.561	-0.002	0.004
d1_glucose_max	0.0003	9.48E-05	3.645	0	0	0.001
d1_glucose_min	0.0003	0	1.303	0.193	0	0.001
d1_hco3_max	-0.0148	0.003	-4.658	0	-0.021	-0.009
d1_hco3_min	-0.0201	0.003	-6.396	0	-0.026	-0.014
d1_heartrate_max	0.0142	0	35.589	0	0.013	0.015
d1_heartrate_min	0.0073	0.001	12.846	0	0.006	0.008
d1_hemoglobin_max	-0.041	0.011	-3.609	0	-0.063	-0.019
d1_hemoglobin_min	-0.0134	0.011	-1.171	0.242	-0.036	0.009
d1_hematocrit_max	-0.0019	0.004	-0.527	0.598	-0.009	0.005
d1_hematocrit_min	0.0199	0.004	5.485	0	0.013	0.027
d1_mbp_max	0.0041	1.00E-03	3.02	0.003	0.001	0.007
d1_mbp_min	-0.0114	0.002	-5.902	0	-0.015	-0.008
d1_platelets_max	0.0007	0	3.277	0.001	0	0.001
d1_platelets_min	-0.0018	0	-7.996	0	-0.002	-0.001
d1_potassium_max	0.2296	0.015	15.709	0	0.201	0.258
d1_potassium_min	-0.0341	0.018	-1.914	0.056	-0.069	0.001
d1_resprate_max	0.0121	0.001	9.626	0	0.01	0.015
d1_resprate_min	0.0575	0.002	26.376	0	0.053	0.062
d1_sodium_max	0.0374	0.003	12.943	0	0.032	0.043
d1_sodium_min	-0.0169	0.003	-5.825	0	-0.023	-0.011
d1_sysbp_max	0.0029	0.001	4.55	0	0.002	0.004
d1_sysbp_min	-0.0166	0.001	18.299	0	-0.018	-0.015
d1_temp_max	-0.0172	0.01	-1.705	0.088	-0.037	0.003
d1_temp_min	-0.3922	0.009	43.999	0	-0.41	-0.375
d1_wbc_max	0.0019	0.001	1.522	0.128	-0.001	0.004
d1_wbc_min	0.0128	0.002	8.042	0	0.01	0.016
elective_surgery	-1.7515	0.025	70.786	0	-1.8	-1.703
height	0.0022	0.002	1.449	0.147	-0.001	0.005
pre_icu_los_days	0.0002	8.47E-05	2.565	0.01	5.13E-05	0
weight	-0.0025	0.001	-3.866	0	-0.004	-0.001

Train = MIMIC

Covariates = SetB

B-splines = False

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	38139
Model:	Logit	Df Residuals:	38098
Method:	MLE	Df Model:	40
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.2163
Time:	21:41:55	Log-Likelihood:	-10367.
converged:	True	LL-Null:	-13228.
		LLR p-value:	0.000
Intercept	11.4961	1.84	6.247
albumin_apache_missing[T.True]	-0.1334	0.049	-2.741
bilirubin_apache_missing[T.True]	-0.465	0.049	-9.524
bun_apache_missing[T.True]	0.8585	0.934	0.92
creatinine_apache_missing[T.True]	0.1392	0.968	0.144
fio2_apache_missing[T.True]	-0.1281	0.058	-2.209
gcs_eyes_apache_missing[T.True]	1.5803	0.285	5.544
gcs_motor_apache_missing[T.True]	0.1359	0.206	0.661
gcs_verbal_apache_missing[T.True]	-0.0725	0.241	-0.301
glucose_apache_missing[T.True]	0.6792	0.36	1.886
heart_rate_apache_missing[T.True]	-1.7983	1.598	-1.125
hematocrit_apache_missing[T.True]	1.4514	0.434	3.341
map_apache_missing[T.True]	1.0225	1.411	0.725
paco2_apache_missing[T.True]	-0.0437	0.061	-0.723
resprate_apache_missing[T.True]	-0.2584	0.621	-0.416
sodium_apache_missing[T.True]	-1.1145	0.595	-1.874
temp_apache_missing[T.True]	-0.7381	0.146	-5.063
urineoutput_apache_missing[T.True]	1.2869	0.134	9.604
wbc_apache_missing[T.True]	-0.6513	0.296	-2.202
albumin_apache	-0.2674	0.038	-6.98
bilirubin_apache	0.0559	0.005	11.591

bun_apache	0.022	0.001	21.225	0	0.02	0.024
creatinine_apache	-0.1753	0.017	10.068	0	-0.209	-0.141
fio2_apache	0.9457	0.11	8.591	0	0.73	1.161
gcs_eyes_apache	-0.4429	0.024	18.089	0	-0.491	-0.395
gcs_motor_apache	-0.0719	0.015	-4.868	0	-0.101	-0.043
gcs_verbal_apache	-0.0914	0.013	-6.984	0	-0.117	-0.066
glucose_apache	0.0004	0	2.601	0.009	0	0.001
heart_rate_apache	0.0065	0.001	8.569	0	0.005	0.008
hematocrit_apache	4.60E-03	4.00E-03	1.295	0.195	2.00E-03	0.012
map_apache	-0.0045	0.001	-6.656	0	-0.006	-0.003
paco2_apache	0.0016	0.003	0.607	0.544	-0.004	0.007
paco2_for_ph_apache	-0.0095	0.003	-3.697	0	-0.014	-0.004
pao2_apache	-0.0007	0	-2.499	0.012	-0.001	0
ph_apache	-1.1167	0.239	-4.679	0	-1.584	-0.649
resprate_apache	0.0295	0.002	14.264	0	0.025	0.034
sodium_apache	0.0025	0.003	0.89	0.374	-0.003	0.008
temp_apache	-0.1124	0.013	-8.875	0	-0.137	-0.088
urineoutput_apache	-0.0003	1.74E-05	18.365	0	0	0.00E+00
ventilated_apache	0.0077	0.062	0.124	0.901	-0.114	0.129
wbc_apache	0.0071	1.00E-03	5.116	0	0.004	0.01

Train = MIMIC

Covariates = SetB

B-splines = True

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	38139
Model:	Logit	Df Residuals:	38084
Method:	MLE	Df Model:	54
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.2431
Time:	13:43:59	Log-Likelihood:	-10012.
converged:	True	LL-Null:	-13228.
		LLR p-value:	0.000

	std	coef	err	z	P> z	[0.025	0.975]
Intercept		-6.6369	4.843	-1.371	0.171	-16.128	2.854
albumin_apache_missing[T.True]		-0.115	0.049	-2.327	0.02	-0.212	-0.018
bilirubin_apache_missing[T.True]		-0.3888	0.05	-7.829	0	-0.486	-0.291
bun_apache_missing[T.True]		0.9932	0.946	1.05	0.294	-0.861	2.847

creatinine_apache_missing[T.True]	-0.0213	0.99	-0.021	0.983	-1.961	1.918
fio2_apache_missing[T.True]	-0.1185	0.059	-1.991	0.046	-0.235	-0.002
gcs_eyes_apache_missing[T.True]	1.4573	0.302	4.828	0	0.866	2.049
gcs_motor_apache_missing[T.True]	0.1375	0.214	0.642	0.521	-0.283	0.557
gcs_verbal_apache_missing[T.True]	-0.1512	0.251	-0.601	0.548	-0.644	0.342
glucose_apache_missing[T.True]	0.5585	0.369	1.513	0.13	-0.165	1.282
heart_rate_apache_missing[T.True]	-1.7511	1.622	-1.08	0.28	-4.93	1.428
hematocrit_apache_missing[T.True]	1.4828	0.444	3.34	0.001	0.613	2.353
map_apache_missing[T.True]	1.3126	1.434	0.915	0.36	-1.499	4.124
paco2_apache_missing[T.True]	0.1408	0.064	2.203	0.028	0.016	0.266
resprate_apache_missing[T.True]	-0.0577	0.622	-0.093	0.926	-1.278	1.162
sodium_apache_missing[T.True]	-1.109	0.603	-1.838	0.066	-2.292	0.074
temp_apache_missing[T.True]	-0.6251	0.153	-4.083	0	-0.925	-0.325
urineoutput_apache_missing[T.True]	1.2571	0.138	9.13	0	0.987	1.527
wbc_apache_missing[T.True]	-0.6765	0.307	-2.202	0.028	-1.279	-0.074
albumin_apache	-0.2391	0.039	-6.058	0	-0.316	-0.162
bilirubin_apache	0.059	0.005	12	0	0.049	0.069
bun_apache	0.0225	0.001	21.135	0	0.02	0.025
creatinine_apache	-		-			
fio2_apache	-0.1903	0.018	10.489	0	-0.226	-0.155
gcs_eyes_apache	0.7332	0.113	6.466	0	0.511	0.955
gcs_motor_apache	-		-			
gcs_verbal_apache	-0.4239	0.025	17.044	0	-0.473	-0.375
bs(glucose_apache, df=3, degree=3) [0]	-0.0587	0.015	-3.861	0	-0.088	-0.029
bs(glucose_apache, df=3, degree=3) [1]	-0.0926	0.013	-6.93	0	-0.119	-0.066
bs(glucose_apache, df=3, degree=3) [2]	0.0934	0.477	0.196	0.845	-0.841	1.028
bs(heart_rate_apache, df=3, degree=3) [0]	1.9652	1.286	1.528	0.127	-0.556	4.487
bs(heart_rate_apache, df=3, degree=3) [1]	-		-		-	-
bs(heart_rate_apache, df=3, degree=3) [2]	5.43E+00	2.75E+00	-1.973	0.048	1.08E+01	-0.037
hematocrit_apache	-9.076	0.803	11.299	0	-10.65	-7.502
bs(heart_rate_apache, df=3, degree=3) [1]	3.9869	0.763	5.228	0	2.492	5.481
bs(heart_rate_apache, df=3, degree=3) [2]	-5.4857	1.593	-3.444	0.001	-8.608	-2.364

bs(map_apache, df=3, degree=3) [0]	-4.091	0.352	11.629	0	-4.78	-3.401
bs(map_apache, df=3, degree=3) [1]	1.2351	0.365	3.386	0.001	0.52	1.95
bs(map_apache, df=3, degree=3) [2]	-2.3062	0.475	-4.858	0	-3.237	-1.376
paco2_apache	-0.0006	0.003	-0.229	0.819	-0.006	0.005
						-
paco2_for_ph_apache		3.00E- -0.0064	03	-2.46	0.014	-0.012
						1.00E- 03
pao2_apache	-0.0005	0	-1.786	0.074	-0.001	4.81E- 05
bs(ph_apache, df=3, degree=3) [0]		2.68E+ -2.5106	00	-0.937	0.349	-7.763
bs(ph_apache, df=3, degree=3) [1]	-7.5489	0.877	-8.605	0	-9.268	-5.83
bs(ph_apache, df=3, degree=3) [2]	-0.6027	1.97E+ 00	-0.306	0.759	-4.459	3.253
bs(resprate_apache, df=3, degree=3) [0]	-0.1478	0.47	-0.315	0.753	-1.069	0.773
bs(resprate_apache, df=3, degree=3) [1]	2.0503	0.3	6.824	0	1.461	2.639
bs(resprate_apache, df=3, degree=3) [2]	0.2683	0.49	0.548	0.584	-0.692	1.228
sodium_apache		-4.09E- 05	0.003	-0.014	0.989	-0.006
bs(temp_apache, df=3, degree=3) [0]	30.594	6.496	4.709	0	17.861	43.326
bs(temp_apache, df=3, degree=3) [1]	9.4111	3.949	2.383	0.017	1.671	17.152
bs(temp_apache, df=3, degree=3) [2]	16.5407	4.695	3.523	0	7.338	25.744
urineoutput_apache	-0.0003	1.73E- 05	18.363	0	0	0
ventilated_apache	-0.0447	0.066	-0.675	0.499	-0.174	0.085
bs(wbc_apache, df=3, degree=3) [0]		6.17E- 1.5081	01	2.443	0.015	0.298
bs(wbc_apache, df=3, degree=3) [1]	4.9622	2.346	2.115	0.034	0.363	9.561
bs(wbc_apache, df=3, degree=3) [2]	2.2194	1.445	1.536	0.124	-0.612	5.051
=====	=====	=====	=====	=====	=====	=====

Train = MIMIC

Covariates = SetA

B-splines = False

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	38139
Model:	Logit	Df Residuals:	38085
Method:	MLE	Df Model:	53
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.1970
Time:	14:22:27	Log-Likelihood:	-10621.
converged:	True	LL-Null:	-13228.
		LLR p-value:	0.000

	coef	std err	z	P> z	[0.025	0.975]
Intercept	4.5022	1.222	3.683	0	2.107	6.898
gender[T.M]	0.0949	0.041	2.308	0.021	0.014	0.175
bmi_missing[T.True]	1.0612	0.403	2.634	0.008	0.272	1.851
d1_creatinine_max_missing[T.True]	1.5323	0.331	4.634	0	0.884	2.18
d1_glucose_min_missing[T.True]	-0.3176	0.35	-0.908	0.364	-1.003	0.368
d1_hco3_max_missing[T.True]	-0.0335	0.314	-0.107	0.915	-0.65	0.583
d1_heartrate_max_missing[T.True]	-0.2728	1.924	-0.142	0.887	-4.044	3.498
d1_hemoglobin_max_missing[T.True]	0.1179	0.242	0.488	0.625	-0.355	0.591
d1_mbp_max_missing[T.True]	1.2105	1.732	0.699	0.485	-2.184	4.605
d1_platelets_max_missing[T.True]	1.027	0.389	2.641	0.008	0.265	1.789
d1_potassium_max_missing[T.True]	0.8247	0.373	2.214	0.027	0.094	1.555
d1_resprate_max_missing[T.True]	-0.643	0.744	-0.864	0.388	-2.102	0.816
d1_sodium_max_missing[T.True]	-0.8453	0.402	-2.104	0.035	-1.633	-0.058
d1_sysbp_max_missing[T.True]	0.0357	0.673	0.053	0.958	-1.284	1.356
d1_temp_max_missing[T.True]	0.2651	0.164	1.613	0.107	-0.057	0.587
d1_wbc_max_missing[T.True]	-0.7187	0.392	-1.835	0.067	-1.486	0.049
height_missing[T.True]	-0.6735	0.4	-1.682	0.093	-1.458	0.111
weight_missing[T.True]	-0.08	0.058	-1.386	0.166	-0.193	0.033
age	0.0025	0	8.952	0	0.002	0.003
bmi	-0.0092	0.004	-2.041	0.041	-0.018	0
d1_creatinine_max	-0.0776	0.046	-1.675	0.094	-0.168	0.013
d1_creatinine_min	0.1888	0.053	3.588	0	0.086	0.292
d1_diasbp_max	-0.0081	0.001	-6.326	0	-0.011	-0.006
d1_diasbp_min	-0.0056	0.002	-2.407	0.016	-0.01	-0.001

d1_glucose_max	0.0002	0	0.658	0.51	0	0.001
d1_glucose_min	0.0037	0	7.88	0	0.003	0.005
d1_hco3_max	0.0213	0.009	2.396	0.017	0.004	0.039
d1_hco3_min	-0.0762	0.008	-8.975	0	-0.093	-0.06
d1_heartrate_max	0.0141	0.001	13.968	0	0.012	0.016
d1_heartrate_min	-5.80E-03	1.00E-03	-4.21	0	8.00E-03	-0.003
d1_hemoglobin_max	-0.046	0.037	-1.242	0.214	-0.119	0.027
d1_hemoglobin_min	-0.3369	0.039	-8.667	0	-0.413	-0.261
d1_hematocrit_max	-0.0021	0.012	-0.166	0.868	-0.026	0.022
d1_hematocrit_min	0.1389	0.013	10.953	0	0.114	0.164
d1_mbp_max	0.0022	0.001	3.513	0	0.001	0.003
d1_mbp_min	-0.0101	0.002	-4.946	0	-0.014	-0.006
d1_platelets_max	0.0017	0.001	3.109	0.002	0.001	0.003
d1_platelets_min	-0.0038	0.001	-6.308	0	-0.005	-0.003
d1_potassium_max	-0.098	2.90E-02	-3.337	0.001	-0.156	4.00E-02
d1_potassium_min	0.2669	0.042	6.401	0	0.185	3.49E-01
d1_resprate_max	0.0265	3.00E-03	9.447	0	0.021	0.032
d1_resprate_min	0.0499	0.005	9.76	0	0.04	0.06
d1_sodium_max	0.0484	6.00E-03	7.918	0	0.036	0.06
d1_sodium_min	-0.0342	0.006	-5.854	0	-0.046	-0.023
d1_sysbp_max	0.0076	0.001	8.396	0	0.006	0.009
d1_sysbp_min	-0.0176	3.30E-02	12.544	0	-0.02	-0.015
d1_temp_max	-	0.024	1.391	0.164	-0.013	0.079
d1_temp_min	-0.2544	0.021	11.928	0	-0.296	-0.213
d1_wbc_max	-0.0099	0.004	-2.462	0.014	-0.018	-0.002
d1_wbc_min	0.0357	0.005	6.565	0	0.025	0.046
elective_surgery	-1.3936	8.80E-02	-	15.796	0	-1.566
height	-0.0077	4.00E-03	-2.449	0.014	-0.014	-0.002
pre_icu_los_days	0.0417	0.03	9.514	0	0.033	0.05
weight	-0.0065	0.001	-5.742	0	-0.009	-0.004

Train = MIMIC

Covariates = SetC

B-splines = False

Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	38139
Model:	Logit	Df Residuals:	38097
Method:	MLE	Df Model:	41
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.1235
Time:	14:40:28	Log-Likelihood:	-11594.
converged:	True	LL-Null:	-13228.
		LLR p-value:	0.000

		std				
	coef	err	z	P> z	[0.025	0.975]
Intercept	25.6624	2.893	8.871	0	19.993	31.332
gender[T.M]	0.0627	0.038	1.635	0.102	-0.012	0.138
bmi_missing[T.True]	0.9975	0.399	2.497	0.013	0.215	1.78
h1_arterial_pco2_max_missing[T.True]	0.2693	0.061	4.446	0	0.151	0.388
h1_bilirubin_max_missing[T.True]	-0.1407	0.066	-2.147	0.032	-0.269	-0.012
h1_creatinine_max_missing[T.True]	-0.0867	0.081	-1.076	0.282	-0.245	0.071
h1_diasbp_min_missing[T.True]	-1.1381	1.097	-1.038	0.299	-3.288	1.012
h1_heartrate_max_missing[T.True]	0.3992	0.175	2.277	0.023	0.056	0.743
h1_lactate_max_missing[T.True]	-0.3413	0.051	-6.638	0	-0.442	-0.241
h1_mbp_min_missing[T.True]	0.5749	0.214	2.689	0.007	0.156	0.994
h1_pao2fio2ratio_min_missing[T.True]	-0.3538	0.067	-5.303	0	-0.485	-0.223
h1_platelets_min_missing[T.True]	0.6045	0.184	3.291	0.001	0.244	0.965
h1_resprate_max_missing[T.True]	-0.9332	0.107	-8.693	0	-1.144	-0.723
h1_sysbp_min_missing[T.True]	0.751	1.08	0.695	0.487	-1.366	2.868
h1_temp_max_missing[T.True]	0.2279	0.073	3.104	0.002	0.084	0.372
h1_wbc_max_missing[T.True]	-0.4512	0.19	-2.38	0.017	-0.823	-0.08
height_missing[T.True]	-0.6762	0.397	-1.702	0.089	-1.455	0.102
weight_missing[T.True]	-0.1471	0.055	-2.696	0.007	-0.254	-0.04
age	0.0037	0	15.176	0	0.003	0.004
bmi	-0.0082	0.004	-2.153	0.031	-0.016	-0.001
elective_surgery	-1.3987	0.087	16.044	0	-1.57	-1.228
h1_arterial_pco2_max	0.001	0.01	0.095	0.924	-0.019	0.021
h1_arterial_pco2_min	-0.0036	0.011	-0.338	0.735	-0.025	0.017
h1_arterial_ph_max	-1.1904	1.241	-0.96	0.337	-3.622	1.241

h1_arterial_ph_min	-1.2512	1.242	-1.007	0.314	-3.686	1.184
h1_arterial_po2_max	-0.0055	0.001	-6.612	0	-0.007	-0.004
h1_arterial_po2_min	0.0046	0.001	5.359	0	0.003	0.006
h1_bilirubin_max	0.0533	0.008	6.862	0	0.038	0.069
h1_creatinine_max	0.0856	0.018	4.848	0	0.051	0.12
					-	
h1_diasbp_min	-1.21E-02	3.00E-03	-4.368	0	1.70E-02	-0.007
h1_heartrate_max	0.0081	0.001	7.285	0	0.006	0.01
h1_lactate_max	0.1774	0.015	11.862	0	0.148	0.207
h1_mbp_min	0.0025	0.003	0.783	0.434	-0.004	0.009
h1_pao2fio2ratio_min	5.79E-06	0	0.027	0.979	0	0
h1_platelets_min	-0.0017	0	-5.862	0	-0.002	-0.001
h1_resprate_max	0.0492	0.003	14.422	0	0.043	0.056
h1_sysbp_min	-0.0071	0.002	-4.603	0	-0.01	-0.004
h1_temp_max	-0.2143	0.023	-9.175	0	-0.26	-0.168
h1_wbc_max	0.0207	3.00E-03	6.5	0	0.014	2.70E-02
					-	
height	-0.0106	0.003	-3.475	0.001	-0.017	5.00E-03
pre_icu_los_days	0.0392	4.00E-03	9.382	0	0.031	0.047
weight	-0.0069	0.001	-6.487	0	-0.009	-0.005

Train = ORCHESTRA
Covariates = SetC
B-splines = False
Logit Regression Results

Dep. Variable:	hospital_death	No. Observations:	59693
Model:	Logit	Df Residuals:	59644
Method:	MLE	Df Model:	48
Date:	Thu, 25 May 2017	Pseudo R-squ.:	0.2231
Time:	14:42:26	Log-Likelihood:	-19092.
converged:	True	LL-Null:	-24577.
		LLR p-value:	0.000

	std					
	coef	err	z	P> z	[0.025	0.975]
Intercept	41.1492	2.624	15.682	0	36.006	46.292
gender[T.M]	0.2056	0.03	6.887	0	0.147	0.264
bmi_missing[T.True]	-0.1304	0.168	-0.776	0.438	-0.46	0.199
gender_missing[T.True]	0.7443	0.986	0.755	0.45	-1.188	2.677
h1_arterial_pco2_max_missing[T.True]	0.0175	0.285	0.061	0.951	-0.542	0.577

h1_arterial_pco2_min_missing[T.True]	0.4694	0.278	1.688	0.091	-0.076	1.015
h1_arterial_ph_max_missing[T.True]	-0.3498	0.21	-1.664	0.096	-0.762	0.062
h1_arterial_ph_min_missing[T.True]	-0.0633	0.261	-0.242	0.809	-0.575	0.448
h1_arterial_po2_max_missing[T.True]	-0.6772	0.287	-2.356	0.018	-1.241	-0.114
h1_arterial_po2_min_missing[T.True]	-0.184	0.314	-0.586	0.558	-0.799	0.431
h1_bilirubin_max_missing[T.True]	-0.2431	0.031	-7.877	0	-0.304	-0.183
h1_creatinine_max_missing[T.True]	0.477	0.073	6.544	0	0.334	0.62
h1_diasbp_min_missing[T.True]	1.295	1.776	0.729	0.466	-2.186	4.776
h1_heartrate_max_missing[T.True]	-0.7402	0.252	-2.935	0.003	-1.234	-0.246
h1_lactate_max_missing[T.True]	-0.1201	0.037	-3.221	0.001	-0.193	-0.047
h1_mbp_min_missing[T.True]	-2.1443	2.089	-1.027	0.305	-6.239	1.95
h1_pao2fio2ratio_min_missing[T.True]	-0.2258	0.076	-2.954	0.003	-0.376	-0.076
h1_platelets_min_missing[T.True]	0.6513	0.101	6.452	0	0.453	0.849
h1_resprate_max_missing[T.True]	0.2348	0.136	1.721	0.085	-0.033	0.502
h1_sysbp_min_missing[T.True]	1.3455	0.957	1.406	0.16	-0.53	3.221
h1_temp_max_missing[T.True]	0.197	0.098	2.001	0.045	0.004	0.39
h1_wbc_max_missing[T.True]	-0.4564	0.105	-4.367	0	-0.661	-0.252
height_missing[T.True]	-0.2422	0.166	-1.46	0.144	-0.567	0.083
pre_icu_los_days_missing[T.True]	0.5576	0.234	2.379	0.017	0.098	1.017
weight_missing[T.True]	0.5438	0.06	9.034	0	0.426	0.662
age	0.0315	0.001	39.555	0	0.03	0.033
bmi	0.0096	0.001	6.528	0	0.007	0.013
elective_surgery	-1.5027	0.042	35.497	0	-1.586	-1.42
h1_arterial_pco2_max	-0.0044	0.002	-2.778	0.005	-0.008	-0.001
h1_arterial_pco2_min	-1.11E-02	3.00E-03	-3.479	0.001	1.70E-02	-0.005
h1_arterial_ph_max	-2.6526	0.208	12.769	0	-3.06	-2.245
h1_arterial_ph_min	-2.9015	0.336	-8.624	0	-3.561	-2.242
h1_arterial_po2_max	0.0048	0	15.28	0	0.004	0.005
h1_arterial_po2_min	4.40E-03	0.001	5.253	0	0.003	0.006
h1_bilirubin_max	0.065	0.006	10.694	0	0.053	0.077
h1_creatinine_max	0.0671	0.007	10.122	0	0.054	0.08
h1_diasbp_min	-0.0817	0.035	-2.366	0.018	-0.149	-0.014

h1_heartrate_max	0.02	0.001	30.276	0	0.019	0.021
h1_lactate_max	0.0182	3.00E-03	5.549	0	0.012	2.50E-02
h1_mbp_min	0.1188	0.052	2.297	0.022	0.017	2.20E-01
h1_pao2fio2ratio_min	-0.0026	0.00E-00	10.121	0	-0.003	-0.002
h1_platelets_min	-9.23E-05	0	-0.694	0.488	0	0
h1_resprate_max	0.0096	2.00E-03	4.479	0	0.005	0.014
h1_sysbp_min	-0.0484	0.017	-2.808	0.005	-0.082	-0.015
h1_temp_max	-0.1208	0.016	-7.368	0	-0.153	-0.089
h1_wbc_max	0.007	0.001	11.411	0	0.006	0.008
height	8.20E-03	0.002	3.264	0.001	0.003	0.013
pre_icu_los_days	0.0097	0.001	10.923	0	0.008	0.011
weight	-0.0178	0.001	12.036	0	-0.021	-0.015
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