Supplementary Material

ICU Patient Scoring System (ICU-PSS)

The six clinical variables were selected, and the five-point qualitative description of ICU patients (A-E) was developed, in conjunction with several ICU specialists in a previous study[1]. The four basic physiological parameters (FiO2, SpO2, Mean arterial pressure, Heart Rate) are used by clinicians as indicators of any appreciable improvement or deterioration in patient condition. The drug fields (Adrenaline and Noradrenaline) indicate the amount of pharmacological support required by the patient.

Supplementary Table 1: High-level description of the ICU-PSS scale.

Class label	Description
A	Patient's cardiovascular system (CVS) normal, with no adrenaline or noradrenaline and low levels of oxygen; urine production often essentially normal (or is well established on renal replacement therapy).
B	Patient CVS nearly normal, probably needs low levels of adrenaline or noradrenaline and oxygen.
C	Patient CVS system is effectively stable; probably on moderate dosages of adrenaline or noradrenaline and oxygen. Most parameters suggest the time-slot is in category A or B, but if any of the following conditions are met, then it should be assigned to category C: - heart rate: moderately low or moderately high; - MAP: moderately low or moderately high; - adrenaline: moderate dose; - noradrenaline: moderate dose; - FiO2: moderate; - SpO2: moderately low.
D	Patient's CVS system is moderately unstable and/or on high doses of adrenaline or noradrenaline or fluid to retain stability. Most parameters suggest the time-slot is in category A or B, but if any of the following conditions are met, then it should be assigned to category D: - heart rate: low or high; - MAP: low or high; - adrenaline: high dose; - noradrenaline: high dose; - FiO2: high; - SpO2: low.
E	Patient's CVS is very unstable (which is usually true in early phases of resuscitation or following a new event) with low BP and high HR or rapidly changing adrenaline or noradrenaline dosage and requires substantial fluid inputs. Most parameters suggest the time-slot is in category A or B, but if any of the following conditions are met, then it should be assigned to category E: - heart rate: extremely low or extremely high; - MAP: extremely low or extremely high; - adrenaline: extremely high dose; - noradrenaline: extremely high dose; - FiO2: extremely high; - SpO2: extremely low.

Balanced Training Datasets

We investigated class-balancing methods to balance the class labels within the annotated datasets during training, through adding the RandomForestClassifier parameter class_weight = balanced. This did not result in a significant performance difference, compared to using the original annotated datasets. The internal and external validation results with this balanced class weight condition are outlined in Supplementary Table 2.

Annotator	Internal Val. F1 micro	External Val. F1 micro
C1	0.600	0.262
C2	0.750	0.541
C3	0.650	0.328
C4	0.700	0.425
C5	0.583	0.230
C6	0.517	0.175
C7	0.550	0.358
C8	0.800	0.423
C9	0.583	0.430
C10	0.650	0.168
C11	0.567	0.302

Supplementary Table 2 : Internal and external validation performance of the Random Forest models across all 11 consultants (C1-C11), using balanced class weights.

Internal Validation

Internal validation metrics were obtained through 5-fold cross validation, utilising the full training dataset. Each trained model was run against the original annotations it learnt from – thus, these internal validation results indicate the 'learnability' of the original annotated datasets, i.e., how well the associations between the attribute variables and provided annotations can be learnt, and in turn how easily the annotator's decision-making can be reproduced.

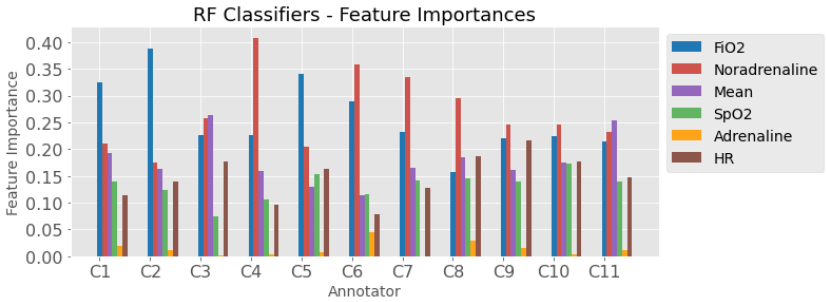
Supplementary Table 3 shows the performance of the optimal RF model for each of the 11 consultant annotators. These models were optimised on F1 micro.

Annotator	F1 micro
C1	0.567
C2	0.717
C3	0.617
C4	0.700
C5	0.583
C6	0.600
C7	0.550
C8	0.767
C9	0.517
C10	0.650
C11	0.500
Majority-Vote (MV)	0.717
Top Majority-Vote (TMV)	0.700

Supplementary Table 3: Internal validation performances for Random Forest models, optimised on F1 micro, trained on the 11 consultants' (C1-C11) annotated datasets.

Feature importance distributions, shown in Supplementary Figure 1, were obtained using the scikit learn feature_importances_property. This is calculated as the normalised total reduction in node impurity (gini or entropy) brought by the feature. For the models with good internal validation performance (F1 micro > 0.7), the

differing feature importance distributions reflect the different rationales and decision-making processes between annotators.



Supplementary Figure 1: Feature importance distributions for Random Forest models, optimised on F1 micro, trained on the 11 consultants' (C1-C11) annotated datasets.

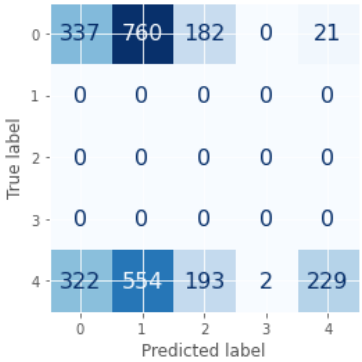
For certain annotators (C4), we can infer Noradrenaline is the most important feature when deciding to annotate a label 'A' classification. For some (C2), FiO2 is most important when making this classification. For others (C10), the rationale is more balanced on Noradrenaline and FiO2.

External Validation

External Validation Experiment 1

Below shows a confusion matrix plot for one of the clinical annotator's (C1) outlining the distribution of the RF predicted labels when run on the HiRID validation dataset. Predicted labels 0-4 correspond to ICU-PSS labels A-E, respectively. True label = 0 corresponds to the patient being discharged alive from ICU within the next hour (i.e., ICU-PSS label 'A'); and true label = 4 corresponds to the patient having died in ICU within the following next hour (i.e., ICU-PSS label 'E').

Supplementary Figure 2 shows C1 correctly classified the patient as 'Discharged Alive' for 337 cases, and correctly classified the patient as 'Discharged Dead' for 229 cases. The trained models were treated as predicting three classes: CL1 = A, CL2 = B/C/D, & CL3 = E.



Supplementary Figure 2: External validation confusion matrix plot for Consultant 1, showing the HiRID dataset true labels and RF model predicted labels. 0 = ICU-PSS label 'A', 4 = ICU-PSS label 'E'.

External Validation Experiment 2: Investigating Time-Series Validation

To assess the performance of the trained DT classifiers on the temporal validation datasets, for each patient timepoint the weighted sum of the five (hourly) ICU-PSS predictions was calculated, and a mean value was

obtained (resulting in 1,064 severity classifications within the temporal datasets). These A-E predicted labels were treated as a 1-5 ordinal scale, therefore the weighted sum values were all in the range 1-5. Again, the trained models were treated as predicting three classes: CL1 = A, CL2 = B/C/D, & CL3 = E.

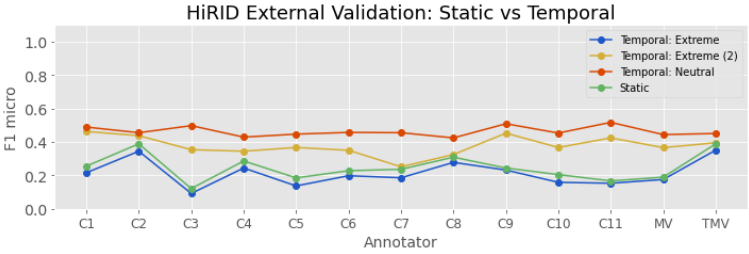
In the main paper, we reported two methods of mapping the weighted sum values (1-5) to these three classes, with differing cut-offs:

i. 'Extreme': CL1 = 1, CL2 = >1-4, CL3 = > 4.

ii. 'Neutral': CL1 = ≤ 3, CL2 = >3-<4, CL3 = ≥ 4.

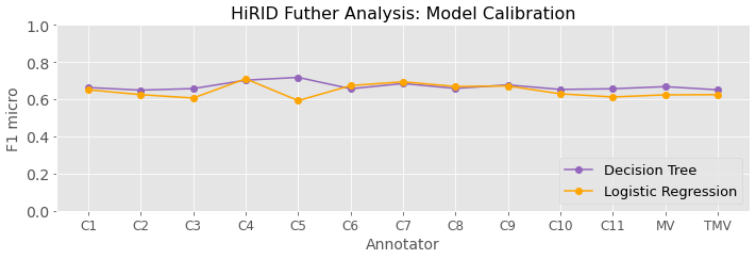
We also investigated an additional 'Extreme (2)' cut-off with weighted sum mapping shown below. These results are outlined in Supplementary Figure 3.

iii. 'Extreme (2)': CL1 = ≤ 2, CL2 = >2-<4, CL3 = ≥ 4.



Supplementary Figure 3: Comparison of the RF classifiers' external validation performance on static vs temporal HiRID validation datasets.

We conducted additional analysis to investigate how supervised-learning models perform on classifying patient discharge status, after training on the predicted labels (A-E) generated on the temporal HiRID dataset. This involved training decision tree and logistic regression models on each consultant's DT classifier predicted labels (A-E) across the five hours before discharge/death for each patient. These results are shown in Supplementary Figure 4.



Supplementary Figure 4: Internal validation performance of the supervised DT and LR models trained on temporal HiRID dataset with predicted labels.

HiRID Pre-processing

The steps to create the HiRID external validation datasets are outlined below. Supplementary Tables 6-15 are included to aid explicability. These do not contain actual HiRID ICU data.

1) Found a broad range of synonyms for the six clinical variables (see Supplementary Table 4). Our medical advisor and co-author (Prof Malcolm Sim) defined an acceptable range of values for each clinical variable, as shown in Supplementary Table 5.

Supplementary Table 4: Common synonyms for the six clinical variables.

Variable name (Glasgow ICU format)	Synonyms
FiO_2	Fraction of Inspired Oxygen
SpO_2	Pulse Oximetry, Oxygen Saturation, Peripheral oxygen
Mean Arterial Pressure	MAP
Heart Rate	-
Adrenaline	Epinephrine
Noradrenaline	Norepinephrine

Supplementary Table 5: Units and acceptable ranges of variables present in the QEUH dataset.

Variable	Acceptable Range	Units
FiO_2	0.21 - 1.0	decimal fraction
SpO_2	0 - 100	%
Mean Arterial Pressure	0 - 200	mmHg
Heart Rate	0 - 300	/min
Adrenaline	0 - 10	mg/hr
Noradrenaline	0 - 10	mg/hr

2) Using HiRID documentation, found all relevant variables to include in data extraction. See Supplementary Table 6.

Supplementary Table 6: Description of variables used in creating the HiRID external validation datasets [2].

Variable	HiRID name	HiRID units	HiRID ID
Adrenaline	Adrenalin	20 µg/ml Perfusor	1000649
	Adrenalin	100 µg/ml Perfusor	1000650
Noradrenaline	Noradrenalin	100 µg/ml Perfusor	1000656
	Noradrenalin	20 µg/ml Perfusor	1000657
FiO_2	Inspired oxygen concentration	%	2010
SpO_2	Peripheral oxygen saturation	%	4000
	Peripheral oxygen saturation	%	8280
Mean Arterial Pressure	Invasive mean arterial pressure	mmHg	110
	Non-invasive mean arterial pressure	mmHg	610
Heart Rate	Heart Rate	/min	200

3)

i. Filtered 'Pharma_records' table for all records with readings for continuous Adrenaline and Noradrenaline (see Supplementary Table 6 for variable IDs).

ii. Grouped each drug variable reading to the closest 15-minute timepoint.

- E.g., Adrenaline reading taken at '2100-01-06 08:34:15' was categorised as '2100-01-06 08:30:00'

iii. Calculated rate of drug administration for Adrenaline/Noradrenaline readings:
- Created 'min_time' field = minimum (earliest) drug administration time within given 15-minute period
- Created 'max_time' field = maximum (latest) drug administration time within given 15-minute period
- Created 'cumulativedose(min_time)' field = cumulative drug dose at 'min_time'
- Created 'cumulativedose(max_time)' field = cumulative drug dose at 'max_time'
- Drug amount administered within each 15-minute period:
  - cumulativedose(max_time) - cumulativedose(min_time) = cumulativedose_diff
- t(diff) = max_time – min_time
- Drug Rate = cumulativedose_diff/ t(diff) (units = micrograms/min)
- Converted rate to into mg/hr (as per training data drug units)

iv. Reformatted drugs table to one record per unique (patientid + timepoint), as per training data structure. See Supplementary Table 7.

Supplementary Table 7: Example of table obtained after Step 3iv. Primary Key = (patientid + timepoint).

patientid	timepoint	Adrenaline	Noradrenaline
01	2198-01-03 18:15:00	0.0	0.2
01	2198-01-03 19:00:00	0.0	0.0
02	2198-01-03 19:45:00	0.1	0.0

4)

i. Filtered 'Observations' table for readings of FiO_2/SpO_2/MAP/HR (see Supplementary Table 6 for variable IDs).
- Note: as this 'Observations' table was too large to process using the facilities available, it was split into ten individual tables ('Observations_1' to 'Observations_10'), each table filtered accordingly, then the results concatenated.

ii. Grouped each physiological variable reading to the closest 15-minute timepoint.
- e.g., FiO_2 reading taken at '2100-01-06 09:56:15' was categorised as '2100-01-06 10:00:00'

iii. Filtered for all unique ICU admission timepoints, which contain readings for <u>all four</u> physiological parameters. This is the pool of relevant (patientid + timepoint) instances, where 'patientid' represents a unique ICU admission and 'timepoint' is the closest 15-minute timepoint to the parameter readings. See Supplementary Table 8.

Supplementary Table 8: Example of table obtained after Step 4iii. PK = (patientid + timepoint)

patientid	timepoint	variableid	pharmaid
01	2198-01-03 18:15:00	[2010 , 200, 4000, 110]	NaN
01	2198-01-03 19:00:00	[110, 4000, 2010, 200]	NaN
02	2198-01-03 19:45:00	[110, 8280, 2010, 200]	1000657

iv. For the (patientid + timepoint) combinations found in Step 4iii, found all records of physiological parameter readings.
- Replaced variable ID numbers by name and listed variable values per unique (patientid + timepoint + variable). See Supplementary Table 9.

Supplementary Table 9: Example of table obtained after Step 4iv. PK = (patientid + timepoint + variable).

patientid	timepoint	variable	value
01	2198-01-03 18:15:00	FiO2	[60.1, 59.5]
01	2198-01-03 18:15:00	HR	[97.0, 98.0, 97.0]
01	2198-01-03 18:15:00	MAP	[87.0, 82.0, 79.0, 85.0]

v. Removed all values outside acceptable range, as specified in Supplementary Table 5.

vi. Extracted minimum, maximum and average parameter values per unique (patientid + timepoint+ variable).

vii. Removed instances where the % variation of values within each 15-minute period was greater than defined cut-off (see Supplementary Tables 10 and 11). As advised by the study's medical advisor, a large variation should not be observed within a such a short time period and is indicative of a data error.

- % variation = ((max_val – min_val) / min_val) x 100

Supplementary Table 10: Defined % variation cut-off

variable	% variation cut-off
FiO_2	5%
SpO_2	10%
MAP	25%
HR	25%

Supplementary Table 11: Example of table obtained after Step 4vii. Primary Key = (patientid + timepoint + variable).

patientid	timepoint	variable	value	min_val	max_val	avg_val	variation(%)
01	2198-01-03 18:15:00	FiO2	[60.1, 59.5]	59.5	60.1	59.8	1.01%
01	2198-01-03 18:15:00	HR	[97.0, 98.0, 97.0]	97.0	98.0	97.3	1.03%
01	2198-01-03 18:15:00	MAP	[87.0, 82.0, 79.0, 85.0]	79.0	87.0	83.3	10.13%

viii. Converted FiO_2 readings from % to decimal fraction (as per training data units).

ix. Reformatted table to one record per unique (patientid + timepoint), as per training data structure, using average parameter values. See Supplementary Table 12.

Supplementary Table 12: Example of table obtained after Step 4ix. Primary Key = (patientid + timepoint).

patientid	timepoint	FiO2	SpO2	MAP	HR
01	2198-01-03 18:15:00	0.60	100.0	83.3	97.3
01	2198-01-03 19:00:00	0.55	96.0	87.0	96.5
02	2198-01-03 19:45:00	0.60	90.0	78.0	98.0

5) Created final HiRID validation dataset by merging the physiological parameter and drug rate tables. See Supplementary Table 13.

Supplementary Table 13: Example of final dataset obtained after Step 5. Primary Key = (patientid + timepoint).

patientid	timepoint	Adrenaline	Noradrenaline	FiO2	SpO2	MAP	HR
01	2198-01-03 18:15:00	0.0	0.2	0.60	100.0	83.3	97.3
01	2198-01-03 19:00:00	0.0	0.0	0.55	96.0	87.0	96.5
02	2198-01-03 19:45:00	0.1	0.0	0.60	90.0	78.0	98.0

6) Found discharge/death times for each unique ICU admission:

- HiRID does not store discharge/death times, therefore the time for the last record of Heart Rate was used as discharge time (if discharge status = alive) or death time (if discharge status = dead). This approach was recommended by the HiRID data owner, Martin Faltys. The discharge status, as well as age, sex and admission time were found in the 'General' table.
- Last recorded time for Heart Rate was found for each unique ICU admission across 'Observations_1' to 'Observations_10'.
- Columns for last hours before discharge/death time (1hr, 2hrs, 3hrs, 4hrs, 5hrs) were added (see Supplementary Table 14). These columns were needed to create the HIRID external validation datasets.

Supplementary Table 14: Example of table obtained after Step 6.

patientid	admission time	discharge _status	d_time*	d_time – 1hr	d_time – 2hrs	d_time – 3hrs	d_time – 4hrs	d_time – 5hrs
01	2198-01-01 15:15:00	alive	2198-01-10 18:33:17	2198-01-10 17:33:17	2198-01-10 16:33:17	2198-01-10 15:33:17	2198-01-10 14:33:17	2198-01-10 13:33:17
02	2197-12-30 19:20:00	dead	2198-01-04 20:12:43	2198-01-04 19:12:43	2198-01-04 18:12:43	2198-01-04 17:12:43	2198-01-04 16:12:43	2198-01-04 15:12:43
03	2198-01-03 04:55:00	alive	2198-01-06 15:37:10	2198-01-06 14:37:10	2198-01-06 13:37:10	2198-01-06 12:37:10	2198-01-06 11:37:10	2198-01-06 10:37:10

*d_time = discharge time (if discharge_status = alive) or death time (if discharge_status = dead)

7) Using the tables created in steps 5 and 6, created individual tables of readings for the following time periods before discharge/death: a) 1hr, b) 2hrs, c) 3hrs, d) 4hrs, e) 5hrs.

- E.g., Filtered Supplementary Table 13 for all readings where (d_time – 1hr) < timepoint < (d_time) to create table of readings within 1hr before discharge/death.

Supplementary Table 15: Example HiRID external validation (static) dataset

patientid	timepoint	Adrenaline	Noradrenaline	FiO2	SpO2	MAP	HR	Discharge/death time	Discharge status
01	2198-01-03 18:15:00	0.0	0.2	0.60	100.0	83.3	97.3	2198-01-03 18:42:12	alive
01	2198-01-03 19:00:00	0.0	0.0	0.55	96.0	87.0	96.5	2198-01-03 23:54:10	dead
02	2198-01-03 19:45:00	0.1	0.0	0.60	90.0	78.0	98.0	2198-01-03 20:05:15	dead

MIMIC-III Pre-processing

The steps to create the MIMIC-III external validation datasets are outlined below. Supplementary Tables 18-22 are included for explicability. These do not contain actual MIMIC-III ICU data.

1) Found relevant variables in MIMIC-III 'd_items' table, by searching variable names and synonyms. See Supplementary Tables 4 and 16.

Supplementary Table 16: Search terms used to find relevant variables within MIMIC-III D_items table.

Variable	Search terms
FiO2	FiO2 | fiO2 | Fio2 | fio2 | FIO2 | FIo2 | inspired | Inspired | Fraction | fraction
SpO2	SpO2 | spO2 | spo2 | SPO2 | oximetry | Oximetry | Peripheral | peripheral
Mean Arterial Pressure	MAP | map | mean | MEAN | Mean
Heart Rate	Heart rate | Heart Rate
Adrenaline	Epinephrin | epinephrin | Adrenalin | adrenalin
Noradrenaline	Norepin | norepin | Noradrenalin

2) From all search results, the study's medical advisor confirmed the acceptable ITEMIDs to include for each variable. See Supplementary Table 17.

Supplementary Table 17: MIMIC-III variable ITEMIDs used in creating external validation dataset.

Variable	MIMIC-III ITEMID
FiO_2	223835, 3420, 3422, 190, 189, 727, 191
SpO_2	646, 220277
Mean Arterial Pressure	52, 224, 438, 443, 456, 6702, 220052, 220181, 224322, 225312
Heart Rate	211, 220045
Adrenaline	221906
Noradrenaline	221289

3)

i. Filtered 'inputevents_cv' and 'inputevents_mv' tables for all records with readings for continuous Adrenaline and Noradrenaline (see Supplementary Table 17 for variable IDs).

ii. Grouped each drug variable reading to the closest 15-minute timepoint.

iii. Reformatted drugs table to one record per unique (icustay_id + timepoint). See Supplementary Table 18.
- Converted 'rate' column from mcg/kg/min to mg/hr (compatible with training data units)
- Checked all rate values are within acceptable range (0-10 mg/hr)
- Renamed ITEMID to drug names

Supplementary Table 18: Example of table obtained after Step 3iii.

subject_id(*1)	hadm_id(*2)	icustay_id(*3)	timepoint	Adrenaline	Noradrenaline
2	10001	22111	2109-01-03 06:00:00	0	1.86
2	10001	22111	2109-01-03 08:00:00	0	0.78
3	10002	22234	2109-01-03 10:00:00	0	0.09

((*1)subject_id = unique patient, (*2) hadm_id = unique hospital admission, (*3) icustay_id = unique ICU stay

4)

i. Filtered 'Chartevents' table for readings of FiO_2/SpO_2/MAP/HR (see Supplementary Table 17 for variable IDs).

- Note: as this 'Chartevents' table was too large to process using the facilities available, it was split into seventeen individual tables ('Chartevents_1' to 'Chartevents_17'), each table filtered accordingly, then the results concatenated.

ii. Grouped each physiological variable readings to the closest 15-minute timepoint.
- E.g., Adrenaline reading taken at '2100-01-06 08:34:15' was categorised as '2100-01-06 08:30:00'

iii. Filtered for all unique hospital admission timepoints, which contain readings for all four physiological parameters. This is the pool of relevant (hadm_id + timepoint) instances, where 'hadm_id' represents a unique hospital admission and 'timepoint' is the closest 15-minute timepoint to the parameter readings. See Supplementary Table 19.

Supplementary Table 19: Example of table obtained after Step 4iii. Primary Key = (hadm_id + timepoint).

hadm_id	timepoint	variableid	pharmaid
10001	2109-01-03 06:00:00	[190, 211, 456, 646]	221289
10001	2109-01-03 08:00:00	[220052, 220045, 220277, 223835]	NaN
10002	2109-01-03 10:00:00	[220045, 220181, 220277, 223835]	221906

iv. For the (hadm_id + timepoint) combinations found in Step 4iii, found all records of physiological parameter readings from the filtered Chartevents table created in Step 4i.
- Removed all rows where 'error' field = 1 (indicates error in measurement).
- Removed all rows where 'icustay_id' field is NULL, keeping only the readings associated with an ICU stay.

v. Converted all FiO_2 ITEMID values where unit=% to decimal fraction.
- FiO_2 ITEMIDs converted: 223835, 727, 191
- Replaced all FiO_2/SpO_2/MAP/HR ITEMID numbers with variable names.

vi. Removed all values outside acceptable range, as specified in Supplementary Table 5.

vii. Extracted minimum, maximum and average parameter values per unique (icustay_id + timepoint + variable).

viii. Removed instances where the % variation of values within each 15-minute period was greater than defined cut-off (see Supplementary Table 10).
- % variation = ((max_val – min_val) / min_val) x 100

ix. Reformatted table to one record per unique (icustay_id + timepoint), as per training data structure (see Supplementary Table 20), using average parameter values. Removed all rows containing null values.

Supplementary Table 20: Example of table obtained after Step 4ix.

subject_id	hadm_id	icustay_id	timepoint	FiO2	SpO2	MAP	HR
2	10001	22111	2109-01-03 06:00:00	0.40	100.0	83.3	97.3
2	10001	22111	2109-01-03 08:00:00	0.40	96.0	87.0	96.5
3	10002	22234	2109-01-03 10:00:00	0.50	90.0	78.0	98.0

5) Created final MIMIC-III validation dataset by merging the physiological parameter and drug rate tables. See Supplementary Table 21.

Supplementary Table 21: Example of final dataset obtained after Step 5. Primary Key = (icustay_id + timepoint).

icustay_id	timepoint	Adrenaline	Noradrenaline	FiO2	SpO2	MAP	HR
22111	2109-01-03 06:00:00	0	1.86	0.40	100.0	83.3	97.3
22111	2109-01-03 08:00:00	0	0.78	0.40	96.0	87.0	96.5
22234	2109-01-03 10:00:00	0	0.09	0.50	90.0	78.0	98.0

6) Found discharge/death times for each unique hospital admission.

- Discharge and death times were found in the 'Admissions' table.
- Created a 'd_time' column, collating discharge and deathtimes
- Created a 'discharge_status' column, where discharge_status = alive when 'dischtime' column is occupied, whilst discharge_status = dead when 'deathtime' column is occupied.
- Columns for last hours before discharge/death time (1hr, 2hrs, 3hrs, 4hrs, 5hrs) were added (see Supplementary Table 22). These columns are needed to create the MIMIC-III external validation datasets.

Supplementary Table 22: Example of table obtained after Step 6.

icustay_id	admittime	discharge_status	d_time*	d_time – 1hr	d_time – 2hrs	d_time – 3hrs	d_time – 4hrs	d_time – 5hrs
22111	2109-01-01 19:26:00	alive	2109-01-04 15:54:00	2109-01-04 14:54:00	2109-01-04 13:54:00	2109-01-04 12:54:00	2109-01-04 11:54:00	2109-01-04 10:54:00
22234	2109-01-02 02:06:00	dead	2109-01-03 17:22:00	2109-01-03 16:22:00	2109-01-03 15:22:00	2109-01-03 14:22:00	2109-01-03 13:22:00	2109-01-03 12:22:00
22456	2109-01-02 20:13:00	alive	2109-01-05 12:13:00	2109-01-05 11:13:00	2109-01-05 10:13:00	2109-01-05 09:13:00	2109-01-05 08:13:00	2109-01-05 07:13:00

7) Using the tables created in steps 5 and 6, created individual tables of readings for the following time periods before discharge/death: a) 1hr, b) 2hrs, c) 3hrs, d) 4hrs, e) 5hrs.

- E.g., Filtered Supplementary Table 21 for all readings where (d_time – 1hr) < timepoint < (d_time) to create table of readings within 1hr before discharge/death

References

1. Sim, M. University of Glasgow (2015).
2. Faltys, M., et al. 'HiRID - high time resolution ICU data set'. (2020).