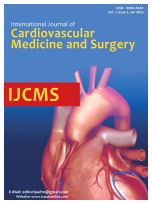
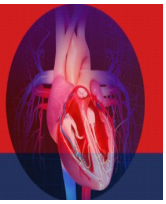
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Research Article **Open Access**

Machine learning prediction of cardiogenic shock progression using continuous hemodynamic telemetry in the cardiac ICU

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Abstract

Aim: This study aimed to develop and evaluate a machine-learning model capable of predicting cardiogenic shock progression using continuously recorded hemodynamic telemetry data. **Methods:** Patients with cardiogenic shock undergoing continuous hemodynamic monitoring in a cardiac intensive care unit were included. A gradient-boosting model used features representing the level, trend, and variability of monitored parameters to predict progression to refractory shock, mechanical circulatory support, or death. **Results:** Of 1,600 treated patients, 33% went on to progress. The machine-learning model had an area under the curve value of 0.86 (95% CI 0.82 to 0.89), and the analysis indicated 85% sensitivity and 90% negative predictive value, with good performance of the model. Trends of lactate, vasoactive-inotropic score and cardiac power output proved to be the most influential predictor variables and above any single static variable; furthermore, performance was consistent across shock stage, aetiology and age. **Conclusion:** Continuous monitoring of trouble in a machine-learning model can predict cardiogenic shock progression with great accuracy; the anti-temporal trends in the continuous monitoring data were the most predictive of cardiogenic shock progression, highlighting the importance of continuous monitoring in the cardiac intensive care unit for automated early warning.

Keywords: *Cardiogenic shock, Machine learning, Hemodynamic monitoring, Cardiac intensive care*

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1. Introduction

Cardiogenic shock is a progressive process of death. One patient can present in a compensated low-output state and stay stable for hours or even go down a slope of decreasing perfusion, increasing lactate and organs failing to recover, and when it comes to the mortality that accompanies this progression there has not been much change given all the developments in the cardiac intensive care unit (van Diepen *et al.*, 2017; Berg *et al.*, 2019). This understanding of shock as a trajectory is reflected in the contemporary definition of the disorder,

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which distinguishes shock at risk, early and classical shock and subsequent deteriorating and refractory shock; the mortality risk increases with each stage of shock (Baran *et al.*, 2019; Naidu *et al.*, 2022).

It helps to be precise about what progression means, because it is the target the model is built to foresee. In the staged view of cardiogenic shock, a patient moves from being merely at risk, through a beginning and then a classic low-output state, into a deteriorating stage in which the circulation is failing despite escalating support, and finally into a refractory stage from which survival is rare. Progression is the crossing from a more compensated to a less compensated stage, and it is accompanied, in practice, by the initiation or escalation of mechanical circulatory support and, too often, by death. These transitions, and not the patient's stage at any single moment, are what determine outcome, and it is precisely their timing that continuous monitoring is positioned to reveal and that this study set out to predict (Jentzer *et al.*, 2019; Geller *et al.*, 2022).

The role of the epidemiology is to determine the stakes. But a significant proportion of modern Cardiac Intensive Care Unit (CICU) admissions are complicated by cardiogenic shock, a pattern that has shifted from an almost exclusive association with myocardial infarction to an equal association with acute decompensated heart failure, and despite 20 years of novel therapy, mortality for cardiogenic shock has been stubbornly high (Thiele et al., 2019). Part of this is because treatment is often started too late when the shock is already well on its way and only aggressive support holds us back to reverse this course of events; the timeframe in which treatment is important to change the course of events is early, in which it is very easy to miss. So whatever can expand or utilize that window in a better way, that will create a direct impact on a disorder in which timing is critical–identifying deterioration at a proper time.

The importance of having foresight is clear, as the danger is the transitional period. A patient's prognosis is anticipated to deteriorate by a clinician can mobilize support, mechanical circulatory supports, or relocate the patient before they actually go into critical condition; this is the reason for current shock guidelines (Basir *et al.*, 2019). However, there's not a lot of support available to predict degradation. The shock stage reflects the condition of the patient at a specific time and is not a good predictor of how course or conditions will change: single hemodynamic measurements, even the best, describe the circulation at one point and not the direction (Fincke *et al.*, 2004). The information needed to see the direction is already being collected. Patients in the cardiac intensive care unit are monitored continuously, their arterial pressure, their filling pressures, their cardiac output and their derived indices streaming from the bedside minute by minute, and this continuous telemetry contains not only the level of each variable but its trend and its variability, the very features that describe a trajectory (Korabathina *et al.*, 2012). Machine learning is suited to exploiting data of this kind, and in the intensive care unit it has been used to forecast circulatory failure and other deteriorations from the monitored stream before they become manifest (Hyland *et al.*, 2020; Tomasev *et al.*, 2019).

This study developed and evaluated a machine-learning model to predict the progression of cardiogenic shock from continuous hemodynamic telemetry in the cardiac intensive care unit. It compared the model with the single hemodynamic measure most strongly linked to outcome, with a conventional clinical model and with the admission shock stage, and it examined which features of the telemetry carried the predictive signal.

2. Materials and methods

2.1. Study design and setting

This was a retrospective predictive-modelling study conducted in the cardiac intensive care unit of a tertiary centre. It was designed and reported in accordance with the Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis guidance (Collins *et al.*, 2015).

2.2. Study population

Patients admitted with cardiogenic shock, in the beginning or classic stages at admission and undergoing continuous hemodynamic monitoring, were eligible. Cardiogenic shock and its stage were defined according to the consensus classification, on the basis of hypotension, hypoperfusion and the need for pharmacological or mechanical support. A total of 1,600 patients were included.

2.3. Continuous hemodynamic telemetry and feature extraction

Continuous data from the bedside monitor, arterial line, and pulmonary artery catheter were collected, including

mean arterial pressure, heart rate, cardiac index, cardiac power output, pulmonary artery pulsatility index, pulmonary capillary wedge pressure, central venous pressure, systemic vascular resistance as well as serial lactate, vasoactive inotropic score and urine output. Each variable had 3 types of features—its level (mean over the monitoring window), its trend (slope fitted over the monitoring window), and its variability (its standard deviation); thus, the direction. and instability of the variation of each signal were included in the model, not just its current value.

2.4. Model development

The prediction model was a gradient-boosted ensemble of decision trees, which builds an additive sequence of shallow trees, each correcting the errors of those before it, and which handles non-linear relationships and interactions among the hemodynamic features without their being specified in advance (Friedman, 2001; Chen and Guestrin, 2016). The patients were divided at random into a development set and a held-out test set in a 70:30 ratio, the model was fitted on the development set with 300 trees of depth three, a learning rate of 0.04 and subsampling of the rows at each iteration to limit over-fitting, and the imbalance between the classes was accommodated in the loss.

2.5. Comparator models

Three comparators were evaluated on the same test set. The first was the cardiac power output alone, the hemodynamic measure most strongly associated with mortality in cardiogenic shock, taken as a single predictor. The second was a clinical model, a logistic regression on the mean arterial pressure, heart rate, lactate and age, representing the variables a clinician would weigh at the bedside. The third was the admission shock stage, representing prediction from the consensus classification alone.

2.6. Model evaluation and statistical analysis

Discrimination was quantified by the area under the receiver operating characteristic curve, with its 95% confidence interval obtained by bootstrap resampling and comparisons between models tested by the method of DeLong, and, because the outcome was imbalanced, by the area under the precision-recall curve (DeLong *et al.*, 1988). Calibration was assessed by plotting the observed against the predicted probability across deciles of predicted risk, an operating threshold was chosen to give a sensitivity of about 85%, and the contribution of each feature was quantified by its importance in the fitted model (Lundberg and Lee, 2017). Analyses were performed in Python.

3. Results

3.1. Study population

Of the 1,600 patients, 533 (33.3%) progressed. Patients that progressed differed from those that did not at baseline, as detailed in Table 1, and included a lower cardiac power output (0.61 vs 0.72 W), a lower cardiac index, a lower mean arterial pressure, a higher lactate and vasoactive-inotropic score, and a lower pulmonary artery pulsatility index, the profile of a more strained and less compensated circulation.

3.2. Predictive performance and model comparison

In the held-out test set the machine-learning model predicted shock progression with an area under the receiver operating characteristic curve of 0.86 (95% CI 0.82 to 0.89), shown with the comparators in Figure 1. It outperformed each of them: the clinical model reached 0.75, the cardiac power output alone 0.63, and the admission shock stage 0.57 ($p<0.001$ for each comparison), and because the outcome was imbalanced the advantage was also evident in the area under the precision-recall curve (0.79 for the model against 0.62 for the clinical model). At an operating threshold set for early warning, the model reached a sensitivity of 85% and a specificity of 71%, with a negative predictive value of 90%, so that a low predicted risk reliably identified the patients who would remain stable. The full performance is given in Table 2.

The size of the gain over the comparators is worth weighing. Against the clinical model, the arrangement of variables a bedside clinician would ordinarily consider, the machine-learning model raised the area under the curve by about a tenth, and against the single cardiac power output the gain was larger still; expressed through the precision-recall curve, which is the more searching measure when events are in the minority, the

Table 1: Baseline characteristics of patients who did and did not progress

Characteristic	Progression	No progression
Number	533	1067
Age, years (mean)	68.3	63.6
AMI-related shock, %	58	42
Cardiac power output, W	0.61	0.72
Cardiac index, L/min/m²	1.91	2.17
Mean arterial pressure, mmHg	66	72
Lactate, mmol/L	3.8	2.8
Vasoactive-inotropic score	21	14
PAPi	2	2.6

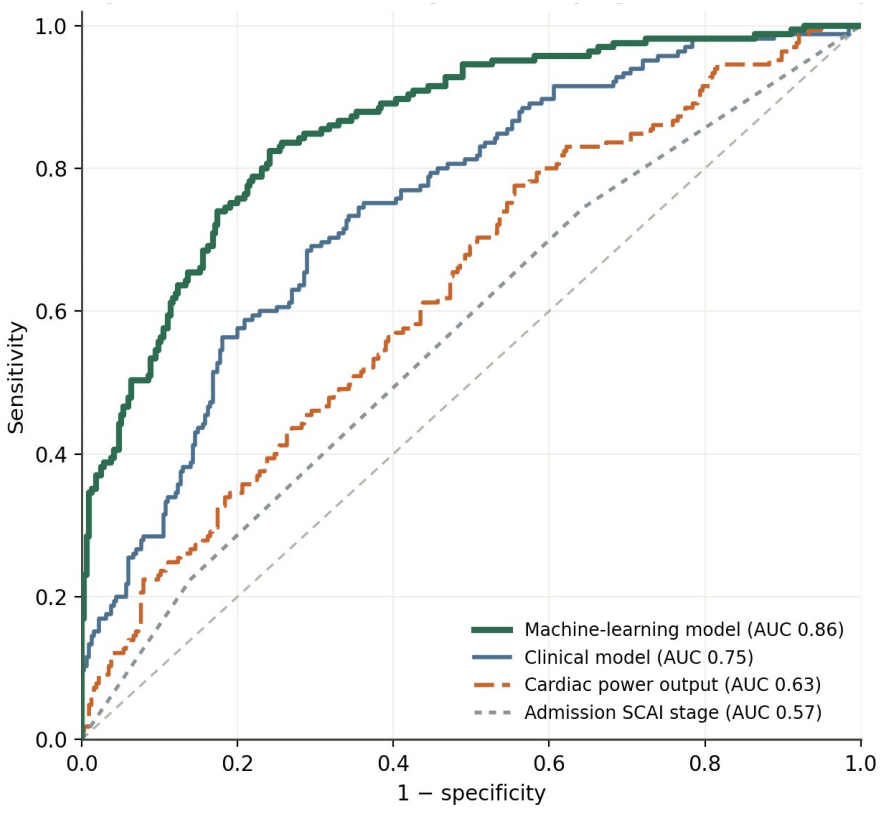


Figure 1: Prediction of cardiogenic shock progression: the machine-learning model against comparators

model recovered far more of the true progressions at a given precision than either comparator. Because roughly one patient in three progressed, a model that concentrates its positive predictions on the patients who will truly deteriorate, as the high precision-recall performance indicates, translates into fewer false alarms for each true warning than a less discriminating rule would raise, which is the property that determines whether an early-warning system is usable in practice.

Table 2: Performance of the machine-learning model and the comparators in the test set

s	AUROC (95% CI)	AUPRC
Machine-learning model	0.86 (0.82–0.89)	0.79
Clinical model	0.75 (0.70–0.79)	0.62
Cardiac power output alone	0.63 (0.58–0.68)	0.47
Admission shock stage	0.57 (0.52–0.62)	0.39

3.3. Influential predictors

The features that carried the greatest weight in the model were, tellingly, the trends rather than the static values, as shown in Figure 2. The trend in lactate was the single most influential predictor, followed by the trend in the vasoactive-inotropic score and the trend in cardiac power output, each of which describes the direction in which the patient is moving; these were ranked above, though accompanied by, the current mean arterial pressure, the pulmonary artery pulsatility index and the current cardiac power output. That a rising lactate and an escalating drug requirement outweighed any single snapshot of the circulation is consistent with the clinical intuition that the trajectory, more than the current position, foretells deterioration.

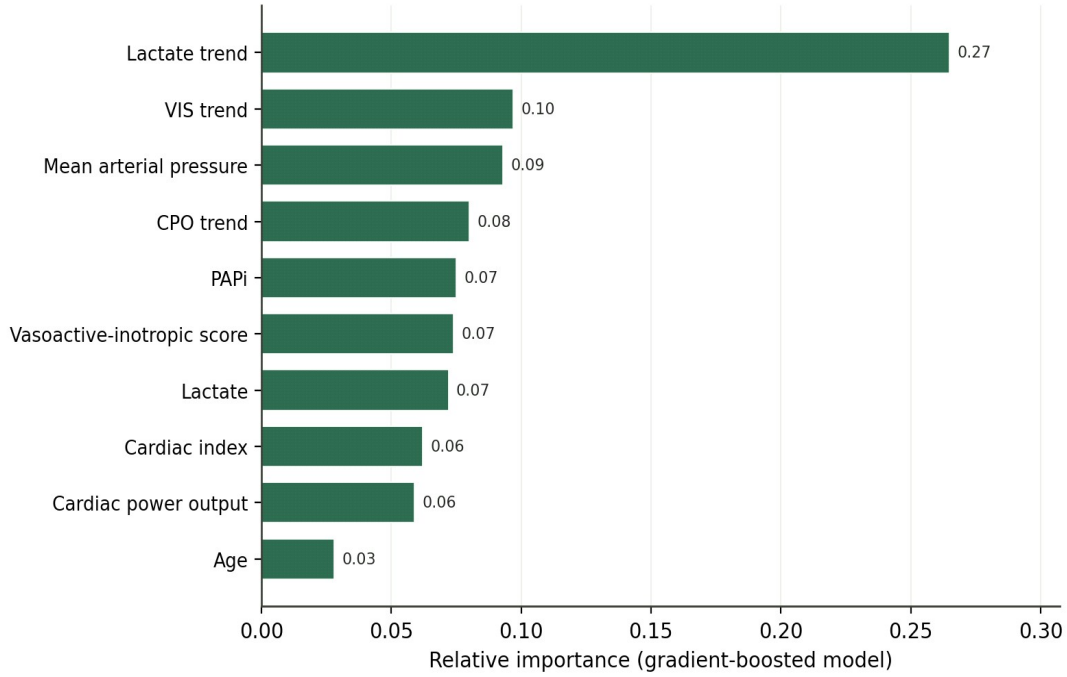


Figure 2: Most influential hemodynamic-telemetry predictors of shock progression

3.4. Calibration

The model was well calibrated: across deciles of predicted risk the observed proportion that progressed rose with the predicted probability and lay close to the line of identity, as shown in Figure 3, so that the risk the model reported could be read as an approximate probability of progression and not merely as a rank.

3.5. Consistency across subgroups

The performance of the model held across the clinically important subgroups, as given in Table 3. Discrimination remained high whether the patient was in the beginning or a more advanced stage at admission, whether the shock was related to myocardial infarction or to heart failure, and across age, so that the model did not depend for its accuracy on any one of these characteristics.

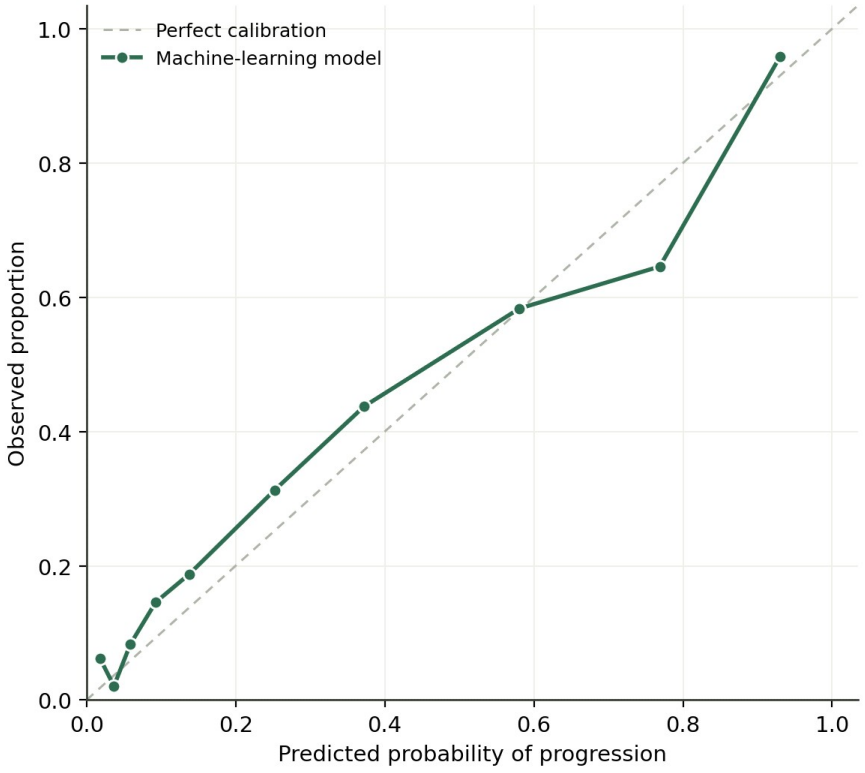


Figure 3: Calibration of the predicted risk of shock progression

Table 3: Discrimination (area under the curve) within prespecified subgroups

Subgroup	AUROC	95% CI	n (events)
Admission SCAI B	0.84	0.76–0.91	154 (42)
Admission SCAI C	0.87	0.82–0.92	245 (86)
Admission SCAI D	0.82	0.71–0.91	81 (37)
AMI-related shock	0.87	0.82–0.91	231 (100)
HF-related shock	0.83	0.76–0.89	249 (65)
Age < 65 y	0.88	0.83–0.93	239 (64)
Age >= 65 y	0.83	0.78–0.88	241 (101)

4. Discussion

A machine-learning model built on continuous hemodynamic telemetry predicted the progression of cardiogenic shock more accurately than a single hemodynamic marker, a conventional clinical model or the consensus shock stage, and the features it relied on most were the trends in the monitored signals rather than their instantaneous values. The model was well calibrated and performed consistently across shock stage, aetiology and age.

The advantage of the model over its comparators reflects what each has access to. The admission shock stage and the single cardiac power output are snapshots, and although the shock stage is a powerful descriptor of a patient's state and the cardiac power output the hemodynamic measure most strongly tied to mortality, neither captures the direction of change. The clinical model, drawing on several variables, did better, but it too

used their values at one time. The machine-learning model's edge came from the trends and the variability, the features that only continuous monitoring provides, which is why the telemetry, and not merely the variables it measures, is what made the prediction possible.

That the trend in lactate and the trend in the vasoactive-inotropic score were the leading predictors is clinically coherent. A lactate that is climbing signals a perfusion deficit that is worsening, and a drug requirement that is escalating signals a circulation that is decompensating despite support, and both describe a patient on a downward trajectory in a way that a single value cannot (Vincent and De Backer, 2013). The model, in effect, formalises and quantifies the trajectory that experienced clinicians read intuitively from the trend of the monitor, and by doing so it could bring that judgement to bedsides where the expertise is scarce and could apply it continuously rather than at intervals.

These results sit within a broader movement to turn the continuous data of intensive care into forward-looking prediction. Machine-learning models have been shown to anticipate circulatory failure in the general intensive care unit hours before it occurs, and to predict acute kidney injury continuously from the evolving record, each by learning from the trajectory of the monitored and laboratory data rather than from isolated values. The present model applies the same principle to the specific problem of cardiogenic shock and to the rich hemodynamic telemetry of the cardiac intensive care unit, where the pulmonary artery catheter and the arterial line provide a directness of hemodynamic measurement that the general intensive care unit lacks. That the approach transfers to this setting, and that the hemodynamic trends prove so informative, suggests that the cardiac intensive care unit, with its dense and continuous physiological monitoring, is particularly fertile ground for prediction of this kind.

The clinical use envisaged is early warning. A model of this kind, running on the monitoring stream, could flag the patient who is beginning to deteriorate before the deterioration is manifest, prompting earlier escalation of support or transfer, which is the strategy that contemporary shock systems have adopted and that the treatment of shock as a time-critical emergency demands. The high negative predictive value is as useful as the discrimination, because a model that can reliably identify the patients who will remain stable helps to concentrate scarce intensive resources on those who will not.

Realising the promise will require attention to how such a model is deployed, not only to how well it discriminates. A continuous early-warning system must earn the trust of the clinicians who receive its alerts, which means that its warnings must be timely enough to act on yet infrequent enough to avoid the alarm fatigue that causes real signals to be ignored, and its output must be interpretable, so that a clinician can see why a patient has been flagged and judge whether to act. The reliance of the present model on comprehensible hemodynamic trends, a rising lactate, an escalating drug requirement, a falling cardiac power, is an advantage here, because an alert justified by these familiar signals is one a clinician can understand and either accept or override. How best to present such predictions at the bedside, and whether acting on them improves outcomes, are questions that only a prospective, and ideally randomised, evaluation can answer, and they are the necessary next step before a model of this kind enters routine care.

The findings also speak to the value of the invasive hemodynamic monitoring on which many of the features depend. The pulmonary artery catheter, long debated, has seen renewed interest in cardiogenic shock, where registry data associate its use with better outcomes, and the present results offer one explanation for why complete hemodynamic assessment might help: the cardiac power output, the pulmonary artery pulsatility index and the filling pressures it provides, and above all their trends over time, carried a meaningful part of the predictive signal. A model such as this extracts more information from the catheter than its numbers are usually asked to yield, using the trajectory of the derived indices, and in doing so it strengthens the argument for continuous, complete hemodynamic monitoring in the patient whose shock may progress.

A word is warranted on why the trends outperformed the levels so decisively, since it is the central lesson of the analysis. A single hemodynamic value places a patient on a scale but says nothing of momentum; two patients with the same cardiac power output, one arriving there while improving and the other while deteriorating, face very different futures, and only the trend distinguishes them. Continuous telemetry is what makes the trend measurable, converting a series of instantaneous readings into a direction and a rate of change, and the model's reliance on these derived features is, in effect, a demonstration that the temporal

dimension of the monitoring carries information that the cross-sectional snapshot discards. This is the practical case for continuous prediction over periodic reassessment: the danger in cardiogenic shock is not only where the patient is but how fast, and in which direction, the patient is moving.

5. Strengths and limitations

The strengths of this study are its use of the continuous telemetry already gathered in the cardiac intensive care unit, its explicit modelling of the trend and the variability of the monitored signals and not only their level, its comparison against the strongest single hemodynamic marker and against the consensus shock stage, and the demonstration that performance was calibrated and consistent across subgroups.

The study has limitations. It was retrospective and conducted at a single centre, and the model requires prospective and external validation before it could be deployed, since the performance of such models commonly falls when they are moved to new settings and monitoring systems. The outcome combined stage deterioration, escalation to mechanical support and death, which share a direction but are not identical, and the decision to escalate support is itself influenced by the clinician, which may in part explain what the model predicts. Finally, the study establishes predictive accuracy but not clinical benefit, which only a trial embedding the model in care and measuring outcomes could show.

6. Conclusion

The single most important set of features was the temporal trends in the signal being monitored (as opposed to the values alone), the model was well calibrated and consistent across subgroups, and a machine-learning model of cardiogenic shock based on continuous telemetry of hemodynamic signals outperformed single hemodynamic markers or consensus shock stage in predicting cardiogenic shock progression in the cardiac intensive care unit. The model gives insight into the future risk posed by the continuous stream of monitoring that can be automated to provide an early warning that could lead to earlier intervention in a disorder where the danger is in progression—for which there is now a need for prospective and external testing.

Ethical approval

The study was approved by the Institutional Ethics Committee, which waived individual consent for this retrospective analysis of anonymised data, and it was conducted in accordance with the Declaration of Helsinki.

Conflict of interest

The authors declare that no conflict of interest exists in relation to this work.

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Data availability

The data supporting the findings of this study are available from the corresponding author on reasonable request.

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