# Artificial intelligence in the perioperative period

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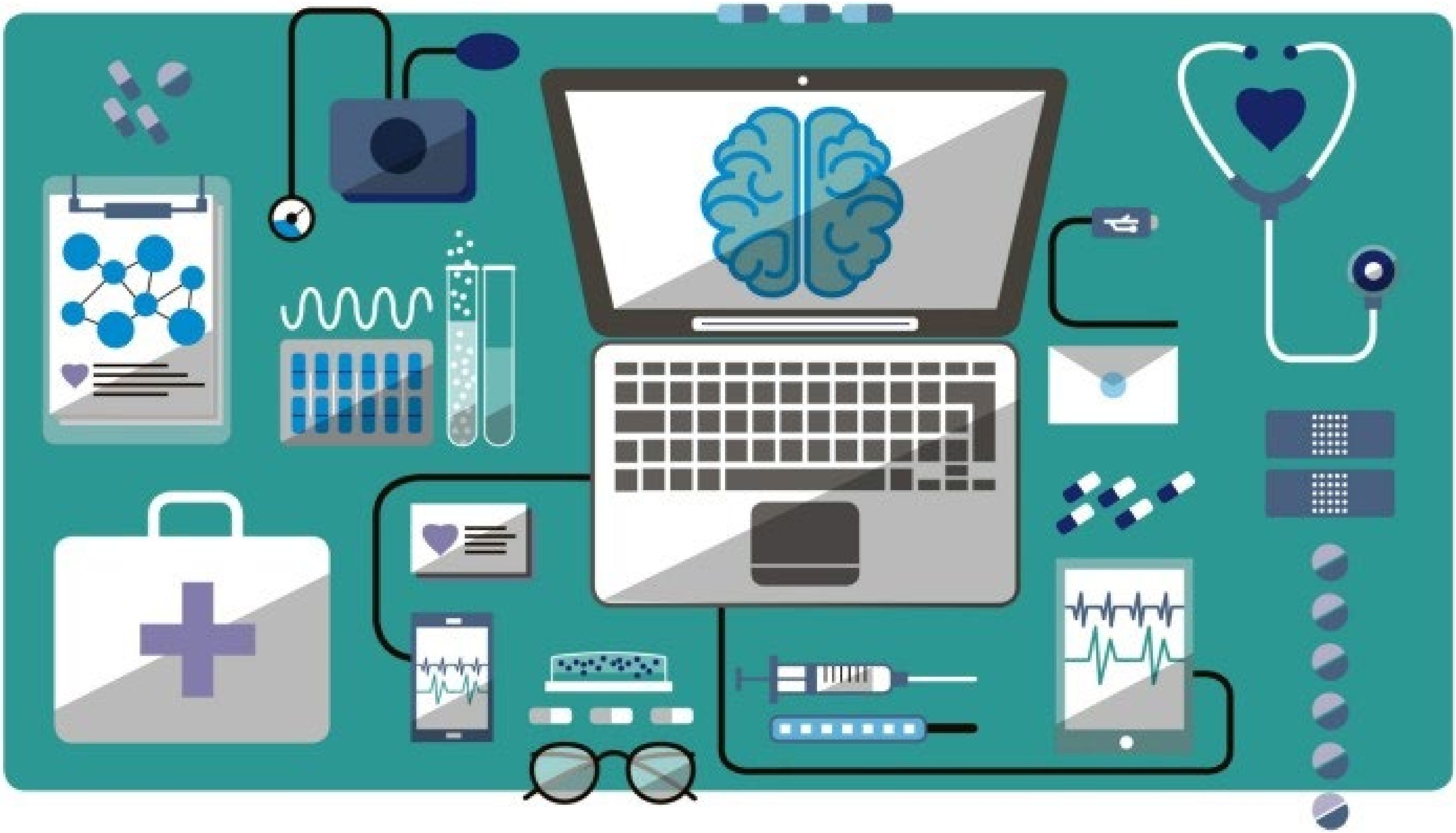
Klinik für Anästhesiologie und operative Intensivmedizin

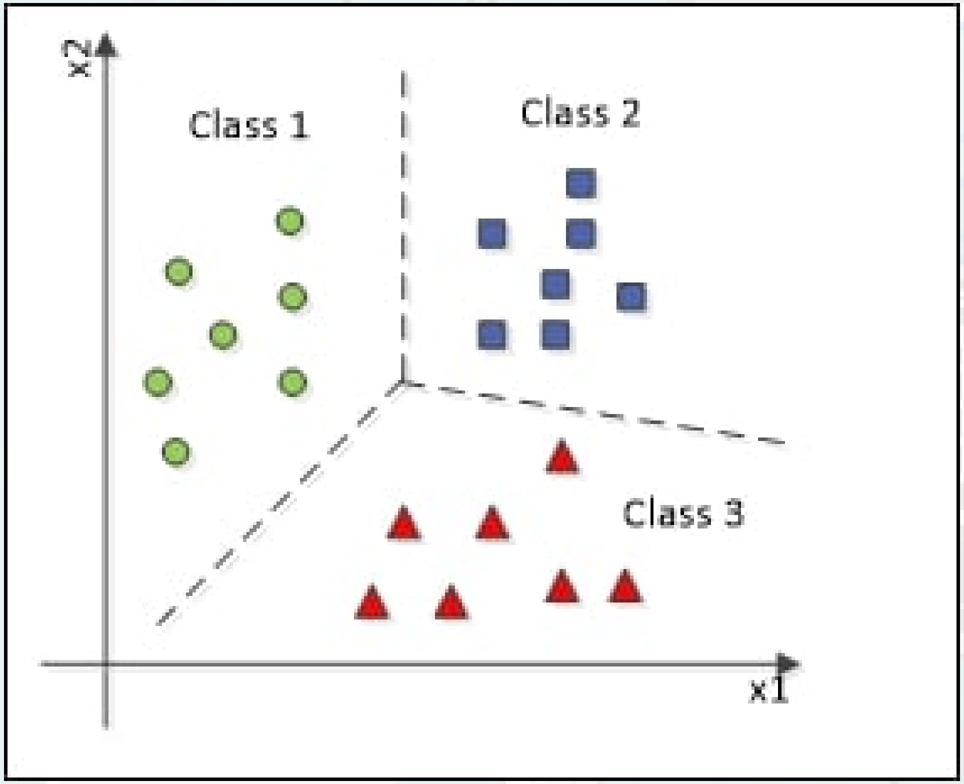
Kepler Universitätsklinikum, Linz

# AI – the common picture

# Reality is much more banal!



# Main usage: Classification

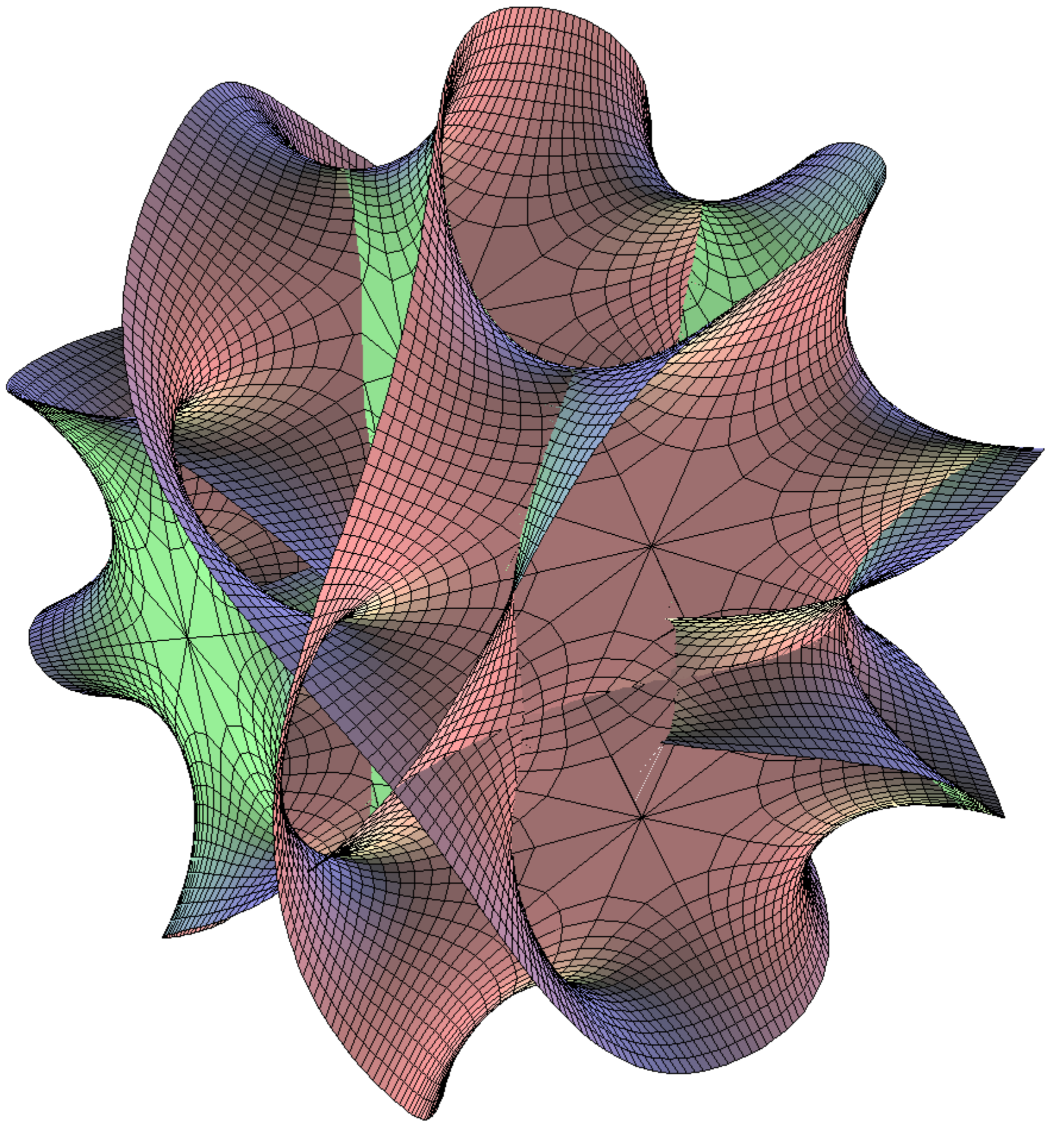



**Patient has a certain diagnosis?**
**Yes / No**

**Patient survives?**
**Yes / No**

**Medication works?**
**Yes / No**

# ML / AI is about multidimensionality



The NEW ENGLAND JOURNAL of MEDICINE
ESTABLISHED IN 1812 FEBRUARY 25, 2021 VOL. 384 NO. 8

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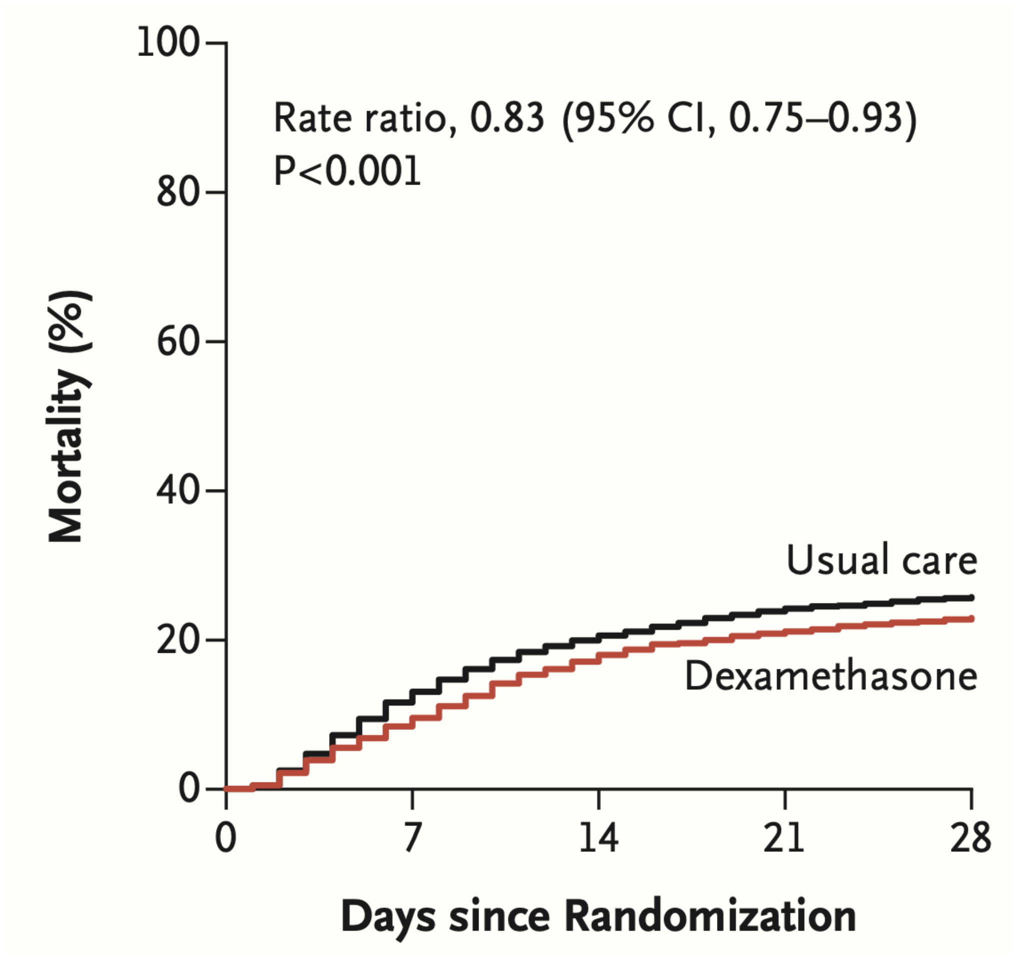
# Dexamethasone in Hospitalized Patients with Covid-19

The RECOVERY Collaborative Group*



# For whom do corticosteroids work?

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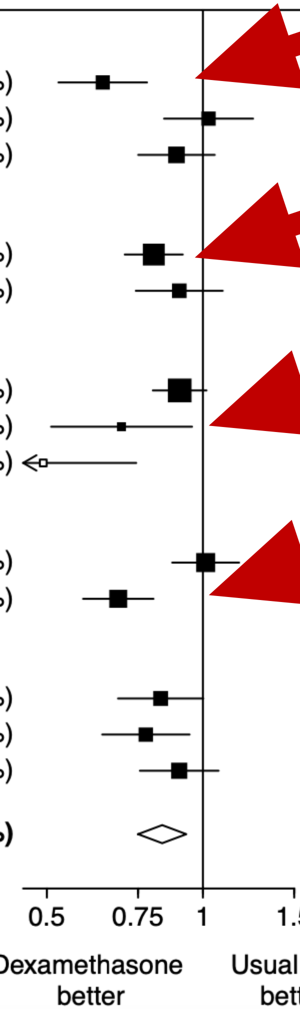
**Figure S1: Effect of allocation to dexamethasone on 28–day mortality by other pre–specified baseline characteristics**

| Characteristic | Dexamethasone | Usual care | RR (95% CI) | Het./trend |
|---|---|---|---|---|
| **Age** | | | | |
| <70 | 129/1141 (11.3%) | 429/2505 (17.1%) | 0.64 (0.53–0.78) | $\chi^2_1$=5.2 |
| ≥70 <80 | 155/469 (33.0%) | 271/859 (31.5%) | 1.03 (0.84–1.25) | |
| ≥80 | 198/494 (40.1%) | 410/957 (42.8%) | 0.89 (0.75–1.05) | |
| **Sex** | | | | |
| Men | 331/1338 (24.7%) | 782/2749 (28.4%) | 0.80 (0.71–0.91) | $\chi^2_1$=0.9 |
| Women | 151/766 (19.7%) | 328/1572 (20.9%) | 0.90 (0.74–1.09) | |
| **Race** | | | | |
| White | 401/1550 (25.9%) | 849/3139 (27.0%) | [illegible] (0.80–1.02) | $\chi^2_1$=2.3 |
| Black, Asian, or minority ethnic group | 52/364 (14.3%) | 160/783 (20.4%) | 0.70 (0.51–0.95) | |
| Unknown | 29/190 (15.3%) | 101/399 (25.3%) | 0.49 (0.33–0.74) | |
| **Days since symptom onset** | | | | |
| ≤7 | 269/916 (29.4%) | 500/1801 (27.8%) | [illegible] (0.87–1.17) | $\chi^2_1$=12.4 |
| >7 | 212/1184 (17.9%) | 604/2507 (24.1%) | 0.69 (0.59–0.80) | |
| **Baseline risk** | | | | |
| <30% | 150/1268 (11.8%) | 378/2683 (14.1%) | 0.83 (0.69–1.00) | $\chi^2_1$=0.4 |
| ≥30% <45% | 147/464 (31.7%) | 334/878 (38.0%) | 0.78 (0.64–0.94) | |
| ≥45% | 185/372 (49.7%) | 398/760 (52.4%) | 0.90 (0.76–1.07) | |
| **All participants** | **482/2104 (22.9%)** | **1110/4321 (25.7%)** | **0.83 (0.75–0.93) p<0.001** | |



# And your patients?

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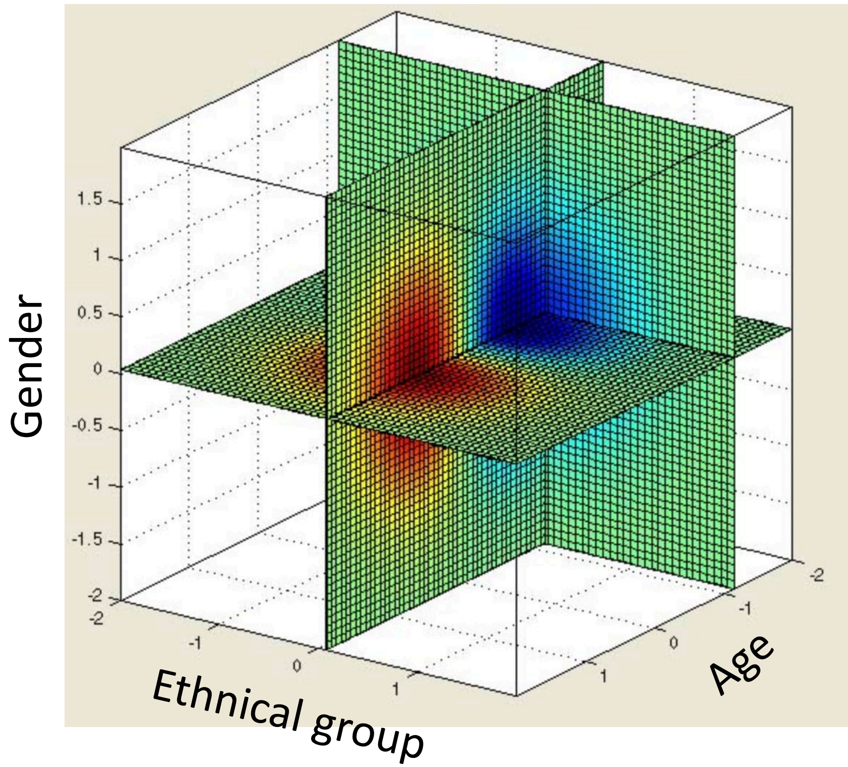
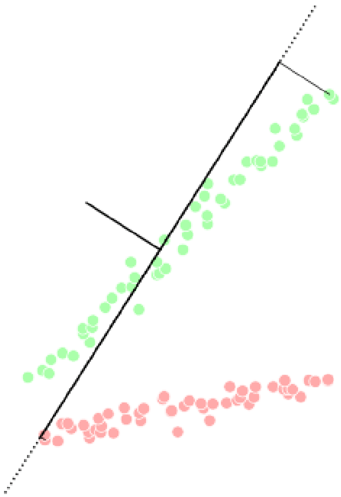
# And your patients?



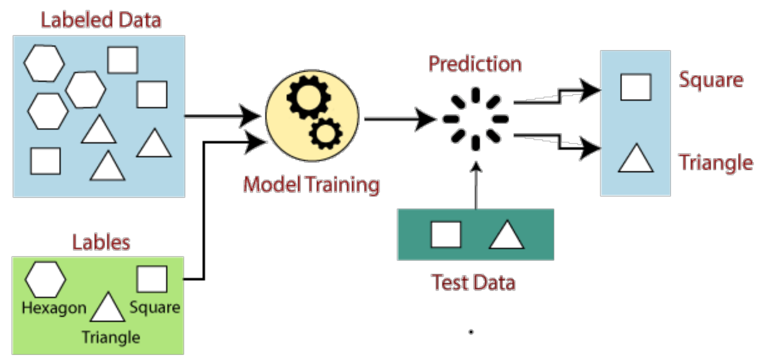
# Multidimensionality explains differences in outcome



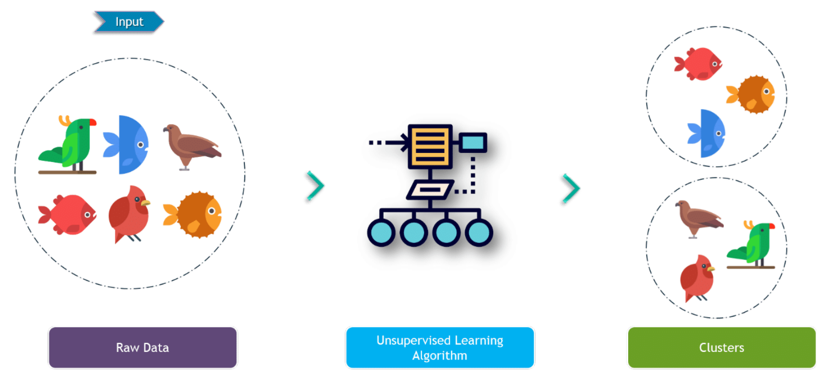



# Three types of machine learning

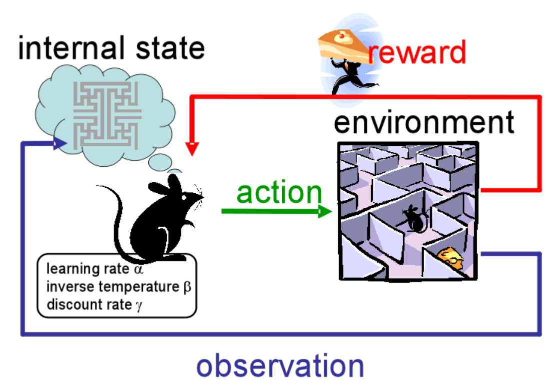
- Supervised learning
  - classification, regression



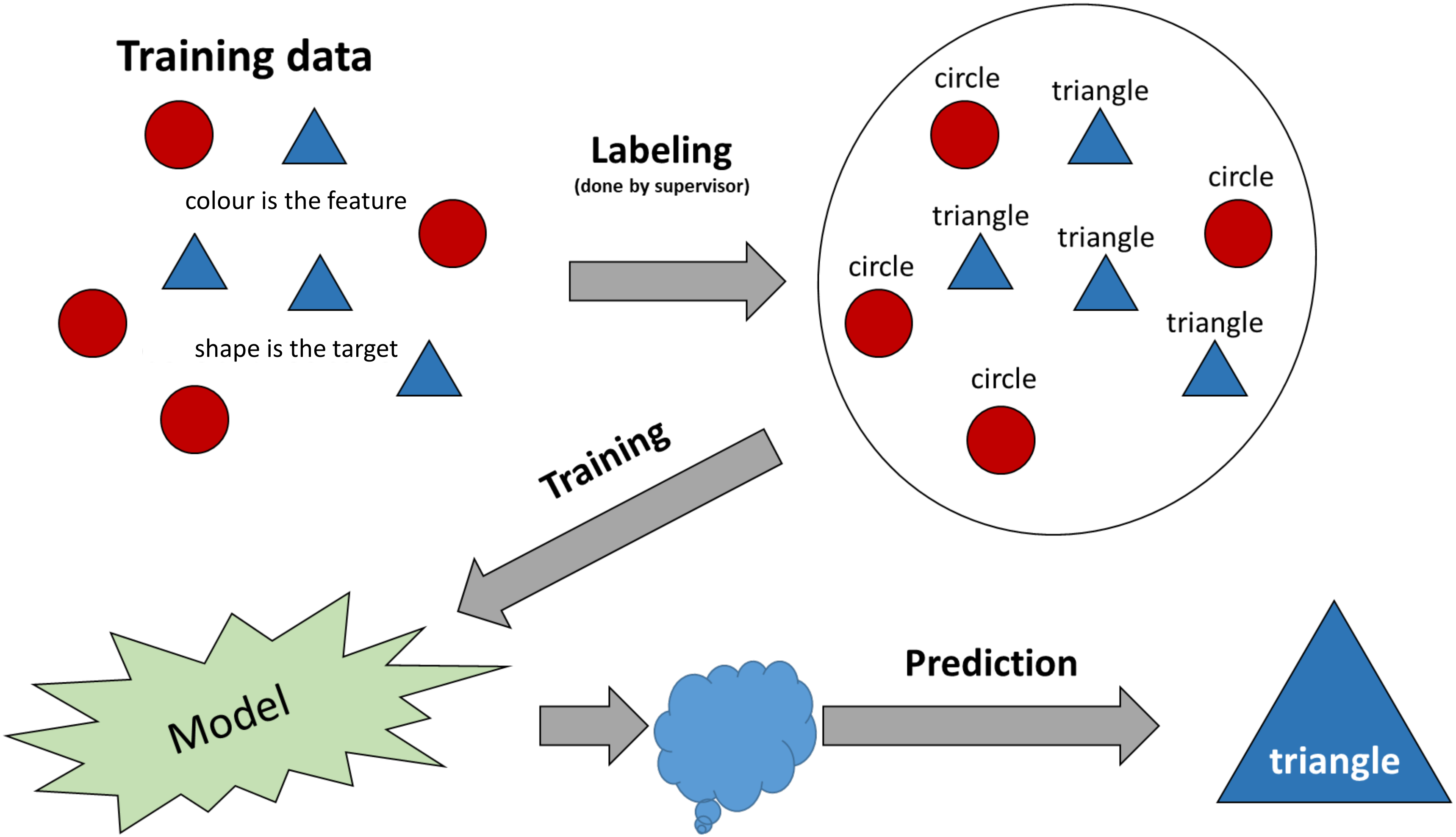

- Unsupervised learning
  - clustering




- Reinforcement learning
  - more general than supervised/unsupervised learning
  - learn from interaction w/ environment to achieve a goal



# Supervised machine learning



# Mortality of heart valve surgery

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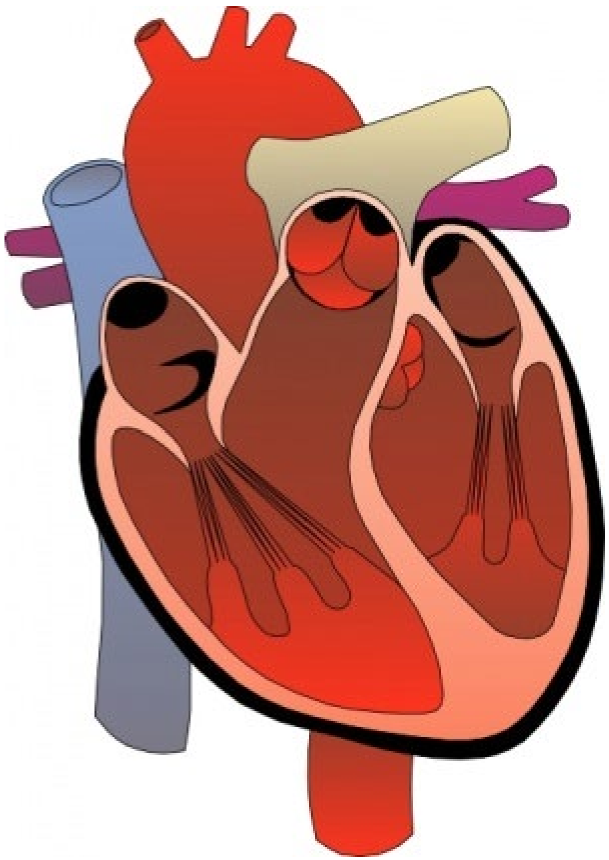


2229 patients

129 preoperative features

**prediction of mortality**

**evaluated prediction models:**

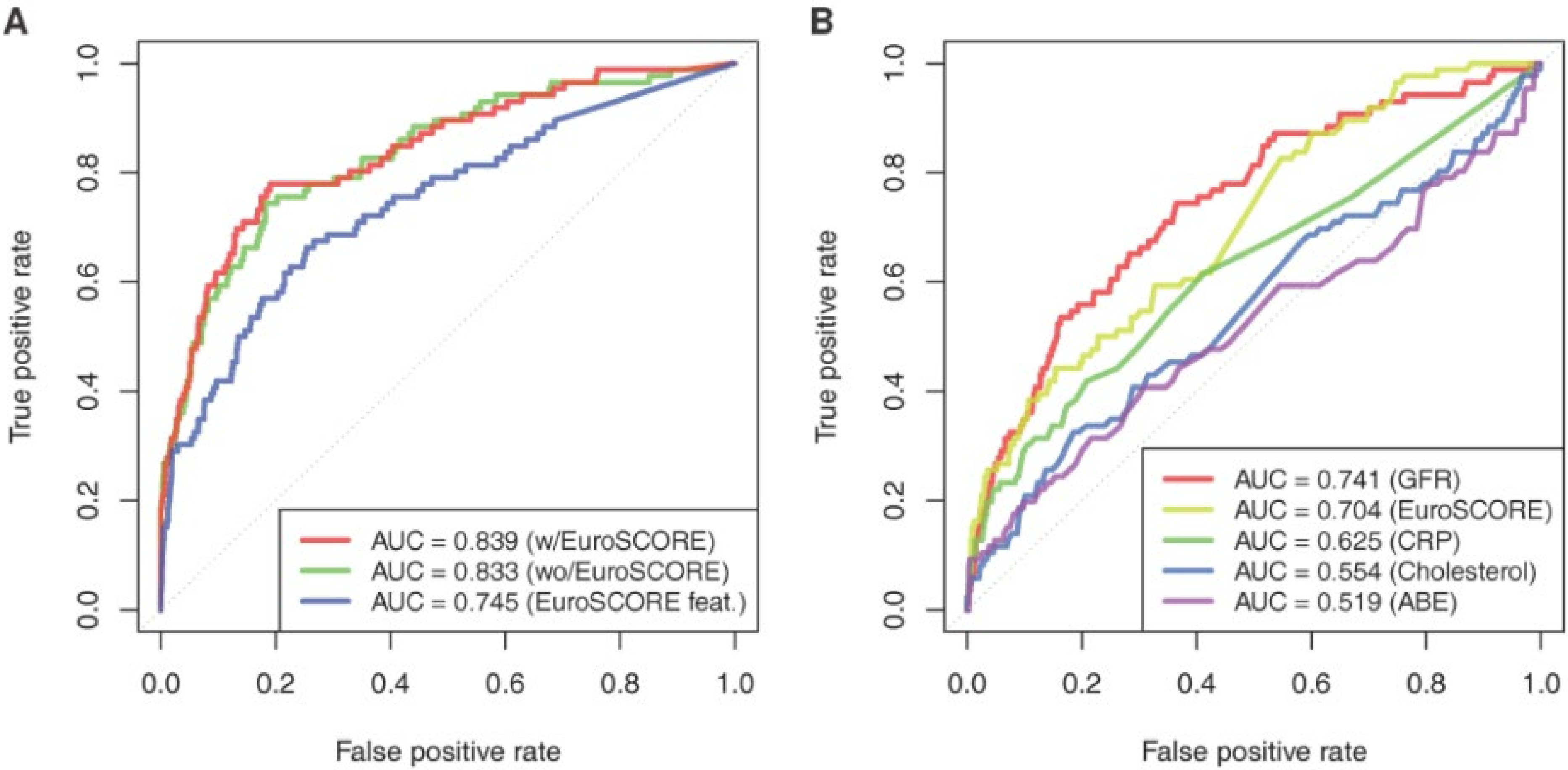
random forests

neural network

support vector machine

Bodenhofer, EJCTS, 2021

# Mortality of heart valve surgery




Bodenhofer, EJCTS, 2021

# Prediction of transfusion

JKU
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Received: 6 December 2019 | Revised: 10 May 2020 | Accepted: 15 May 2020
DOI: 10.1111/trf.15935

Check for updates

TRANSFUSION

ORIGINAL RESEARCH

## Machine learning–based prediction of transfusion

**Andreas Mitterecker[1] | Axel Hofmann[2] | Kevin M. Trentino[3] | Adam Lloyd[3] | Michael F. Leahy[4] | Karin Schwarzbauer[1] | Thomas Tschoellitsch[5] | Carl Böck[5] | Sepp Hochreiter[1] | Jens Meier[5]**

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[3]Data and Digital Innovation, East Metropolitan Health Service, Perth, Australia

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### Abstract

**Background:** The ability to predict transfusions arising during hospital admission might enable economized blood supply management and might furthermore increase patient safety by ensuring a sufficient stock of red blood cells (RBCs) for a specific patient. We therefore investigated the precision of four different machine learning–based prediction algorithms to predict transfusion, massive transfusion, and the number of transfusions in patients admitted to a hospital.

**Study Design and Methods:** This was a retrospective, observational study in three adult tertiary care hospitals in Western Australia between January 2008

# Prediction of transfusion

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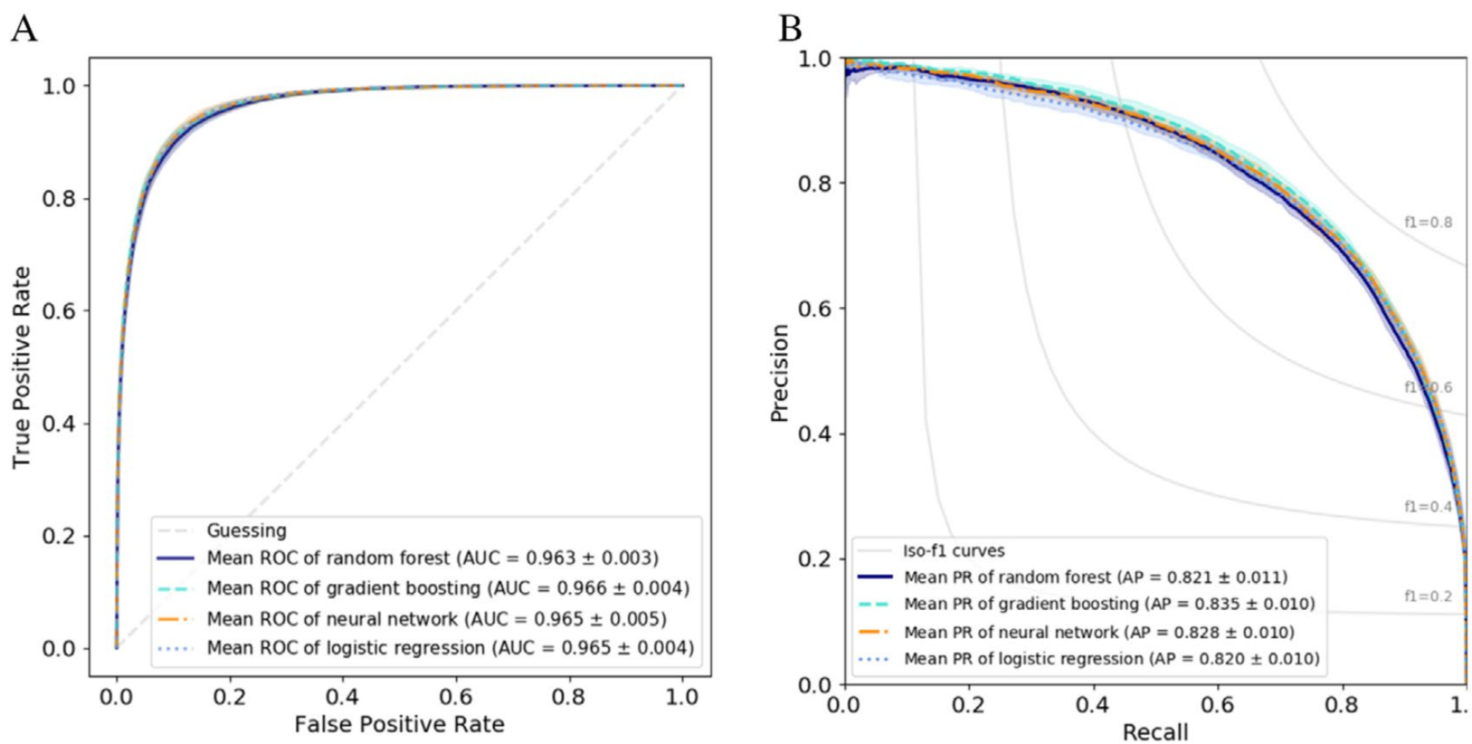
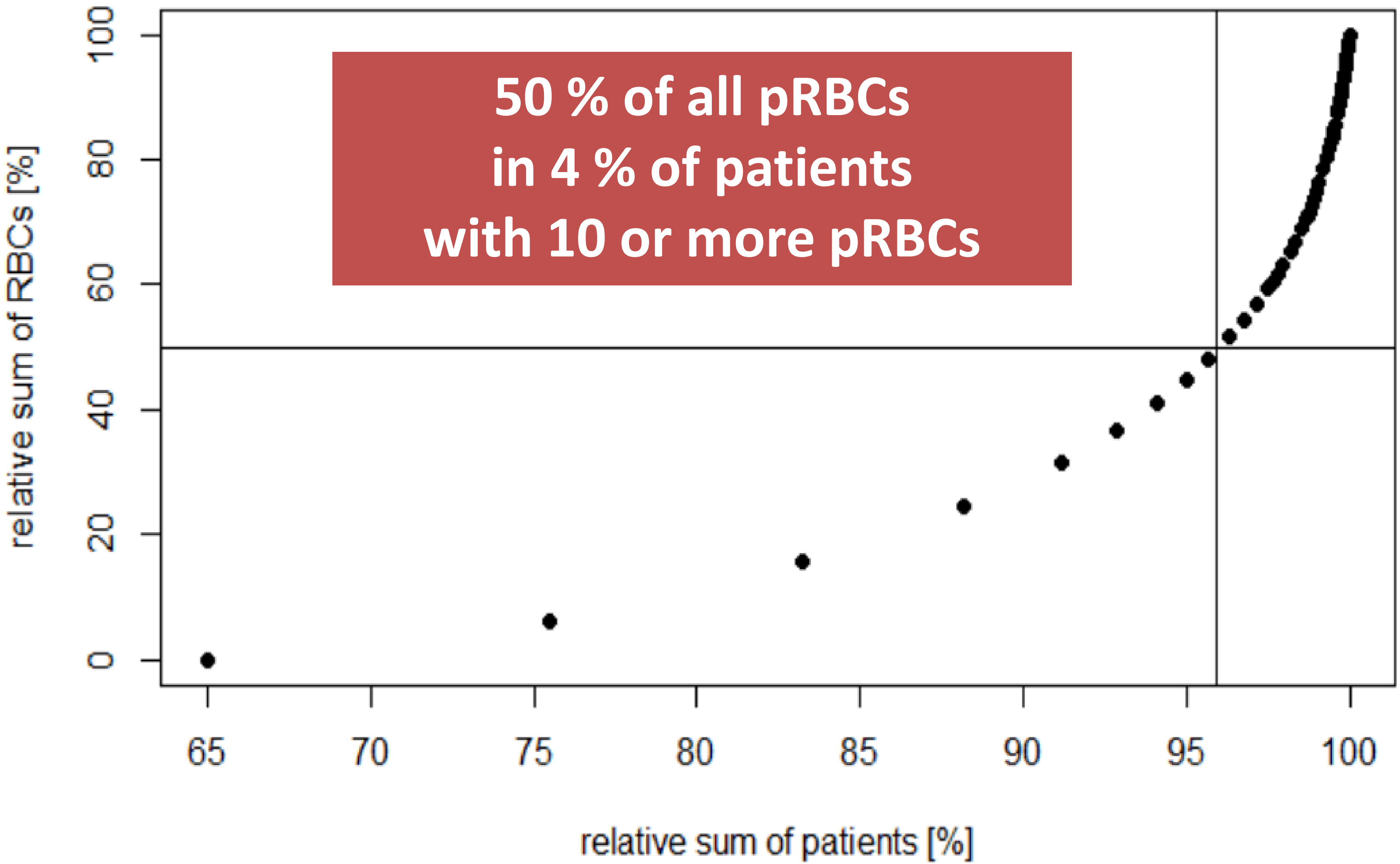
**TABLE 2** Prediction of transfusion

| Method | AUC | AP | BA | Sens | Spec | Prec | NPV | $F_1$ |
|---|---|---|---|---|---|---|---|---|
| Neural network | 0.966 (± 0.004) | 0.828 (± 0.012) | **0.870 (± 0.008)** | **0.898 (± 0.007)** | 0.958 (± 0.009) | 0.719 (± 0.022) | **0.970 (± 0.006)** | 0.749 (± 0.006) |
| Logistic regression | 0.965 (± 0.005) | 0.820 (± 0.011) | 0.856 (± 0.006) | 0.894 (± 0.012) | **0.966 (± 0.009)** | **0.749 (± 0.008)** | 0.966 (± 0.004) | 0.748 (± 0.010) |
| Random forest | 0.963 (± 0.004) | 0.821 (± 0.011) | 0.858 (± 0.004) | 0.584 (± 0.006) | 0.964 (± 0.006) | 0.737 (± 0.011) | 0.966 (± 0.006) | 0.743 (± 0.006) |
| Gradient boosting | **0.966 (± 0.003)** | **0.835 (± 0.013)** | 0.864 (± 0.008) | 0.872 (± 0.006) | 0.965 (± 0.005) | 0.747 (± 0.025) | 0.968 (± 0.007) | **0.755 (± 0.007)** |



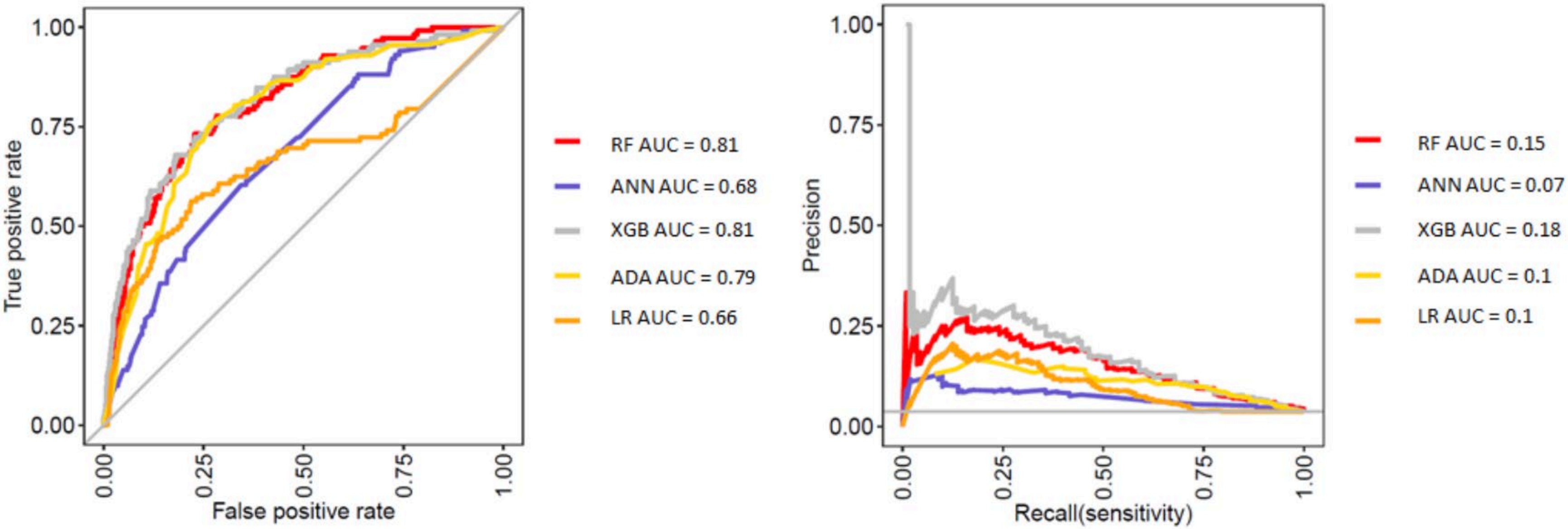

Mitterecker, Transfusion, 2019

# Massive transfusion in cardiac surgery




Tschoellitsch, EJA, 2022

# Massive transfusion in cardiac surgery




| | PPV | NPV | AUC ROC | AUC $F_1$-score |
|---|---|---|---|---|
| ***all features*** | | | | |
| RF | 0.110 (0.09-0.13) | 0.987 (0.98-0.99) | 0.810 (0.76-0.86) | 0.150 |
| ANN | 0.065 (0.05-0.08) | 0.977 (0.97-0.98) | 0.680 (0.62-0.74) | 0.070 |
| XGB | 0.126 (0.1-0.16) | 0.985 (0.98-0.99) | 0.810 (0.76-0.86) | 0.180 |
| ADA | 0.099 (0.08-0.12) | 0.987 (0.98-0.99) | 0.790 (0.74-0.84) | 0.100 |
| LR | 0.090 (0.07-0.11) | 0.979 (0.97-0.98) | 0.660 (0.6-0.72) | 0.100 |

Tschoellitsch, EJA, 2022

# Machine Learning Prediction of SARS-CoV-2 Polymerase Chain Reaction Results with Routine Blood Tests

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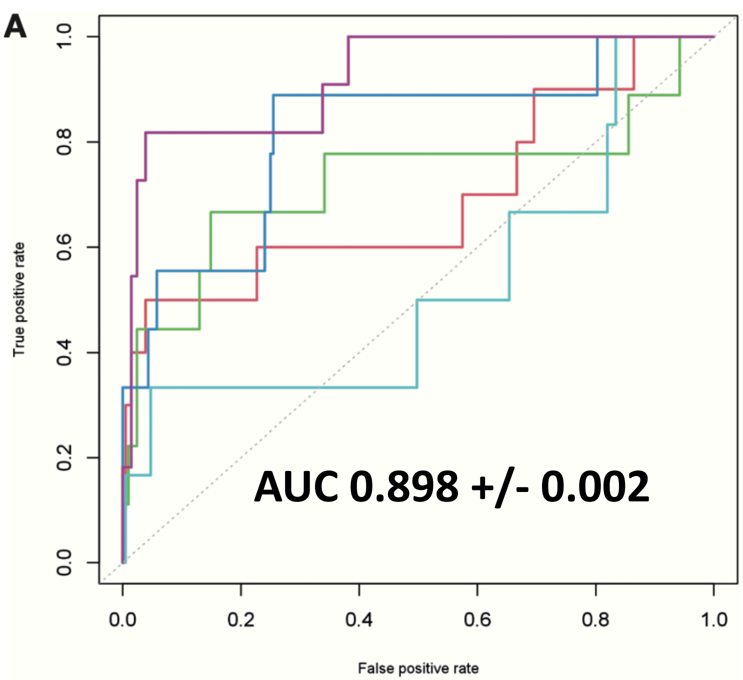
*Thomas Tschoellitsch, MD,*[1] *Martin Dünser, MD,*[1] *Carl Böck, MSc,*[1] *Karin Schwarzbauer, MSc,*[2] *Jens Meier, MD*[1,*]

*Laboratory Medicine* 2021;52:146-149

DOI: 10.1093/labmed/lmaa111




## Table 2. Confusion Matrix for Model Results

| Confusion Matrix | Actual Positive | Actual Negative |
|---|---|---|
| Predicted positive (%) | 34 (6.8 ± 3.2) | 232 (46.4 ± 9.6) |
| Predicted negative (%) | 20 (4 ± 0.7) | 1071 (214.2 ± 9.1) |
| Accuracy: 86.1% (%) | PPV: 20.0 | NPV: 98.8 |

*NPV, negative predicted value; PPV, positive predicted value.*
*First number: All folds; parentheses: mean and standard variance per fold.*

# Unsupervised machine learning

# Unsupervised machine learning

# Typical classification

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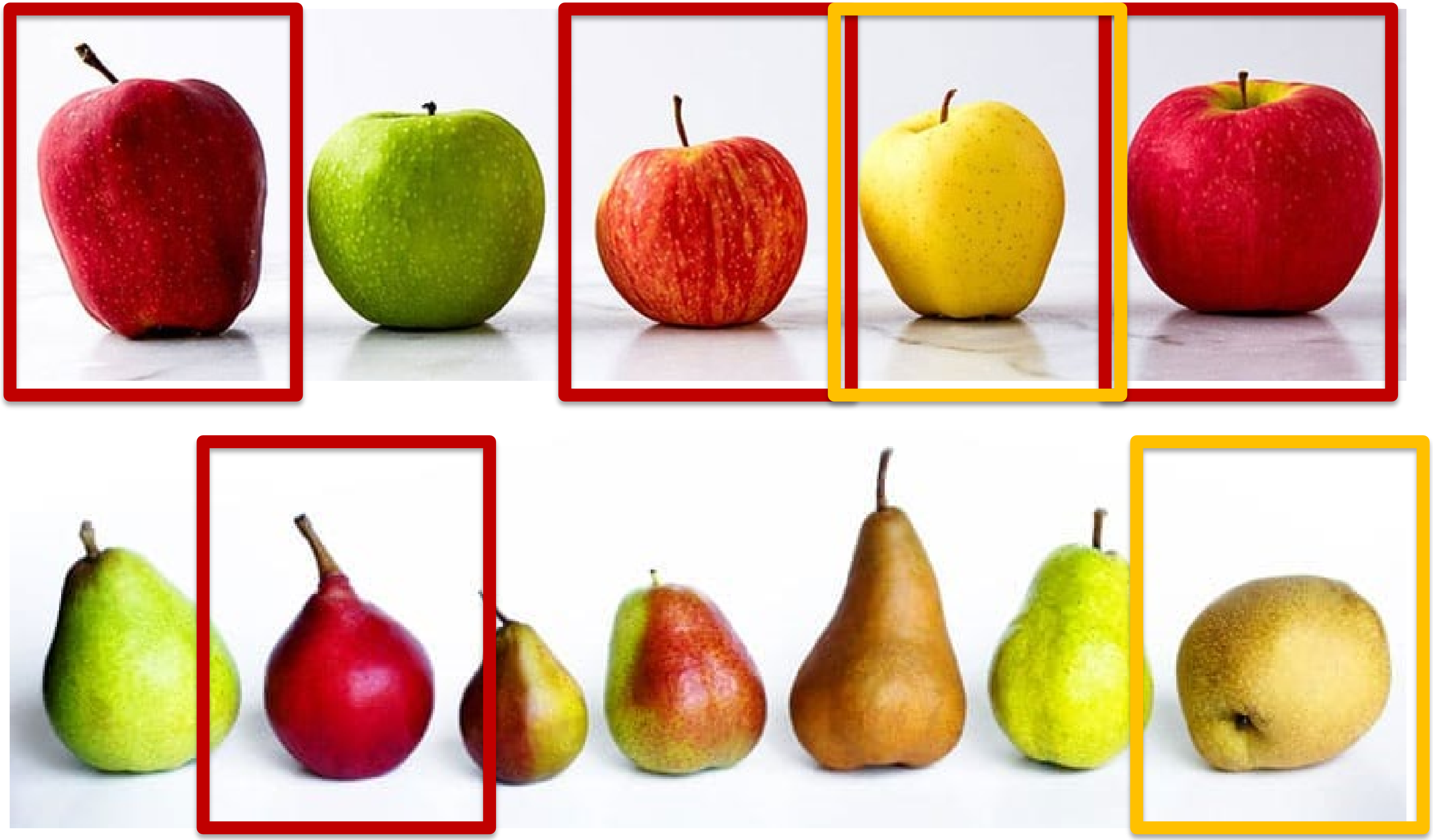
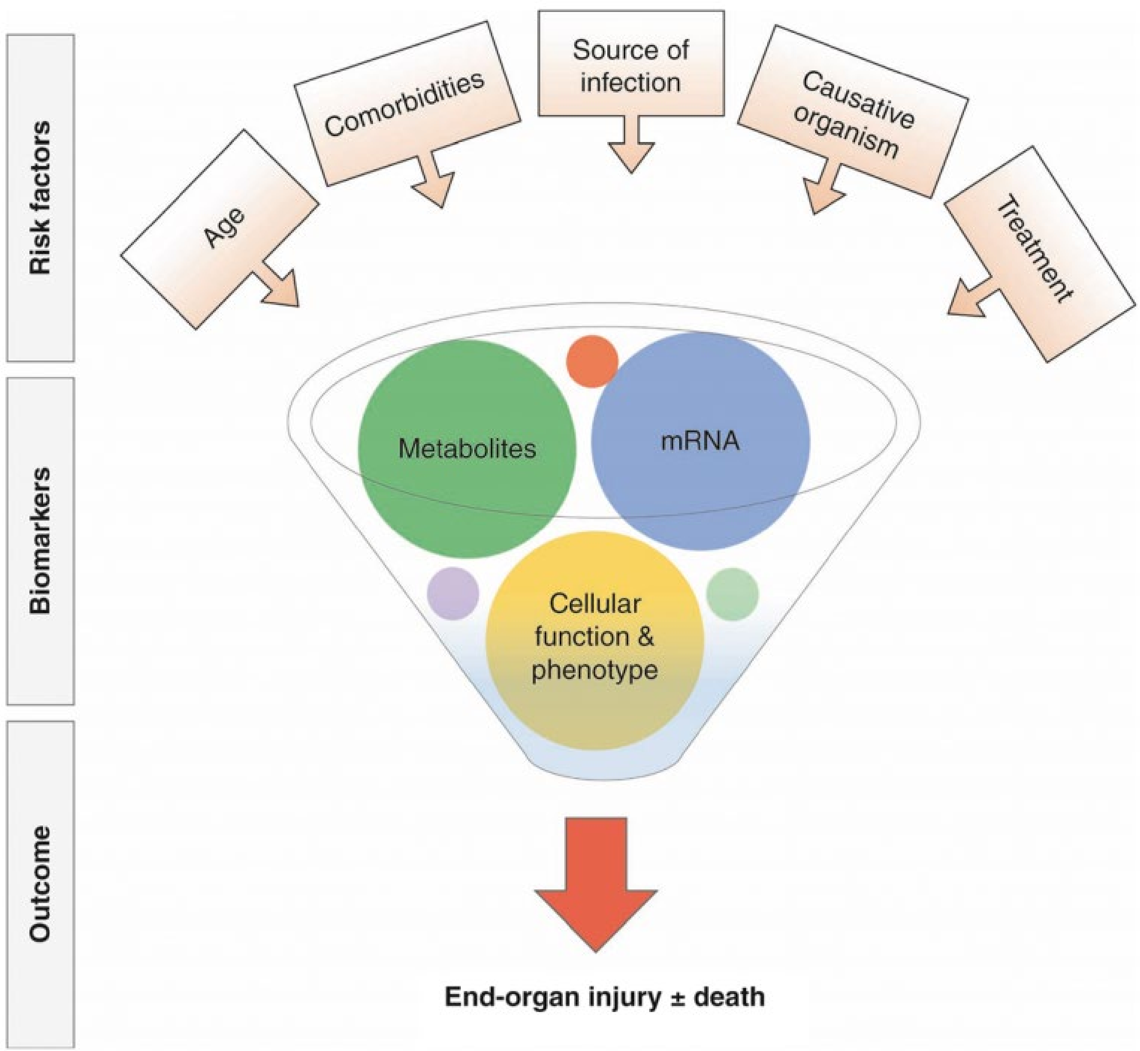
# Alternative truth.....

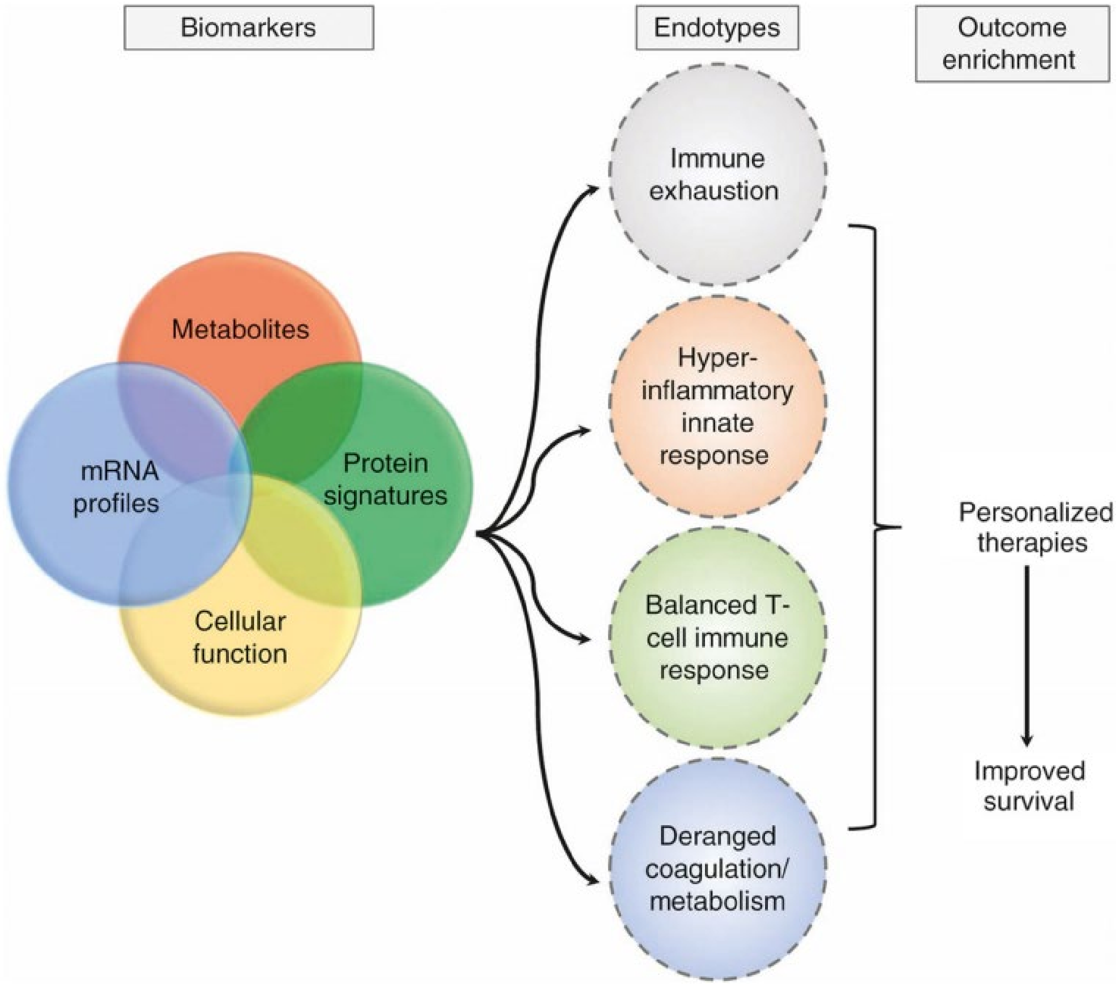


# Example:
# Differences in septic patients




Leligdowicz, Crit Care, 2019

# Example:
# Differences in septic patients




Leligdowicz, Crit Care, 2019

# Are all ICU patients the same?

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## Identifying Distinct Subgroups of ICU Patients: A Machine Learning Approach

Kelly C. Vranas, MD[1,2]; Jeffrey K. Jopling, MD, MSHS[1,3]; Timothy E. Sweeney, MD, PhD[4]; Meghan C. Ramsey, MD[1,5]; Arnold S. Milstein, MD, MPH[1]; Christopher G. Slatore, MD, MS[6,2]; Gabriel J. Escobar, MD[7]; Vincent X. Liu, MD, MS[7]

**Objectives:** Identifying subgroups of ICU patients with similar clinical needs and trajectories may provide a framework for more efficient ICU care through the design of care platforms tailored around patients' shared needs. However, objective methods for identifying these ICU patient subgroups are lacking. We used a machine learning approach to empirically identify ICU patient subgroups through clustering analysis and evaluate whether these groups might represent appropriate targets for care redesign efforts.

**Design:** We performed clustering analysis using data from patients' hospital stays to retrospectively identify patient subgroups from a large, heterogeneous ICU population.

**Setting:** Kaiser Permanente Northern California, a healthcare delivery system serving 3.9 million members.

**Patients:** ICU patients 18 years old or older with an ICU admission between January 1, 2012, and December 31, 2012, at one of 21 Kaiser Permanente Northern California hospitals.

**Interventions:** None.

[1]Department of Medicine, Clinical Excellence Research Center, Stanford University, Stanford, CA.

[2]Division of Pulmonary and Critical Care, Department of Medicine, Oregon Health and Science University, Portland, OR.

[3]Department of Surgery, Stanford University, Stanford, CA.

# Identifying Distinct Subgroups of ICU Patients: A Machine Learning Approach

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## Description of the clusters

| Patient Subgroup Characteristics | Cluster 1 (*n* = 1,933; 38.7%) Relatively Healthy, Short-Stay ICU Patients | Cluster 2 (*n* = 622; 12.4%) Older Patients Suffering Catastrophic Illness | Cluster 3 (*n* = 1,250; 25.0%) Postsurgical and Postprocedural Patients | Cluster 4 (*n* = 897; 17.9%) Older Patients Discharged With Long-Term Care Needs | Cluster 5 (*n* = 207; 4.1%) Prior Healthy Patients With Prolonged Stay and Good Recovery | Cluster 6 (*n* = 91; 1.8%) Patients With Severe Illness and Desire for Limits of Life-Sustaining Therapy |
|---|---|---|---|---|---|---|
| Patient | | | | | | |
| Age (yr) | 60.9 ± 17.1 | 72.7 ± 14.1 | 63.8 ± 15.0 | 74.8 ± 12.7 | 58.7 ± 16.3 | 79.4 ± 11.6 |
| Male, % | 54.6 | 52.1 | 60.0 | 47.5 | 54.1 | 53.9 |
| Comorbidity (Comorbidity Point Score, version 2) | 44 ± 46 | 65 ± 52 | 35 ± 35 | 63 ± 54 | 48 ± 49 | 70 ± 54 |
| Hospitalization | | | | | | |
| Emergency department admission, % | 100.0 | 86.8 | 21.5 | 82.8 | 79.7 | 100.0 |
| Most common diagnosis | Sepsis (19.8%) | Sepsis (38.9%) | **Acute myocardial infarction** (10.1%) | Sepsis (27.6%) | Sepsis (24.6%) | Sepsis (28.9%) |
| Need for procedure, % | 0.2 | 9.7 | **76.9** | 17.2 | 19.8 | 4.4 |
| Code status, % | | | | | | |
| Do not resuscitate | 0.0 | 18.0 | 0.0 | 28.2 | 0.0 | 0.0 |
| Partial code | 0.0 | 0.8 | 0.0 | 0.0 | 0.5 | **100.0** |
| Predicted hospital mortality, % | 4.8 ± 7.6 | **16.5 ± 19.0** | 1.9 ± 3.0 | 9.4 ± 11.9 | 8.1 ± 11.6 | **22.5 ± 19.7** |

Vranas, CCM, 2017

Intensive Care Med (2015) 41:814–822
DOI 10.1007/s00134-015-3764-7

ORIGINAL

CrossMark

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Daniel B. Knox
Michael J. Lanspa
Kathryn G. Kuttler
Simon C. Brewer
Samuel M. Brown

# Phenotypic clusters within sepsis-associated multiple organ dysfunction syndrome

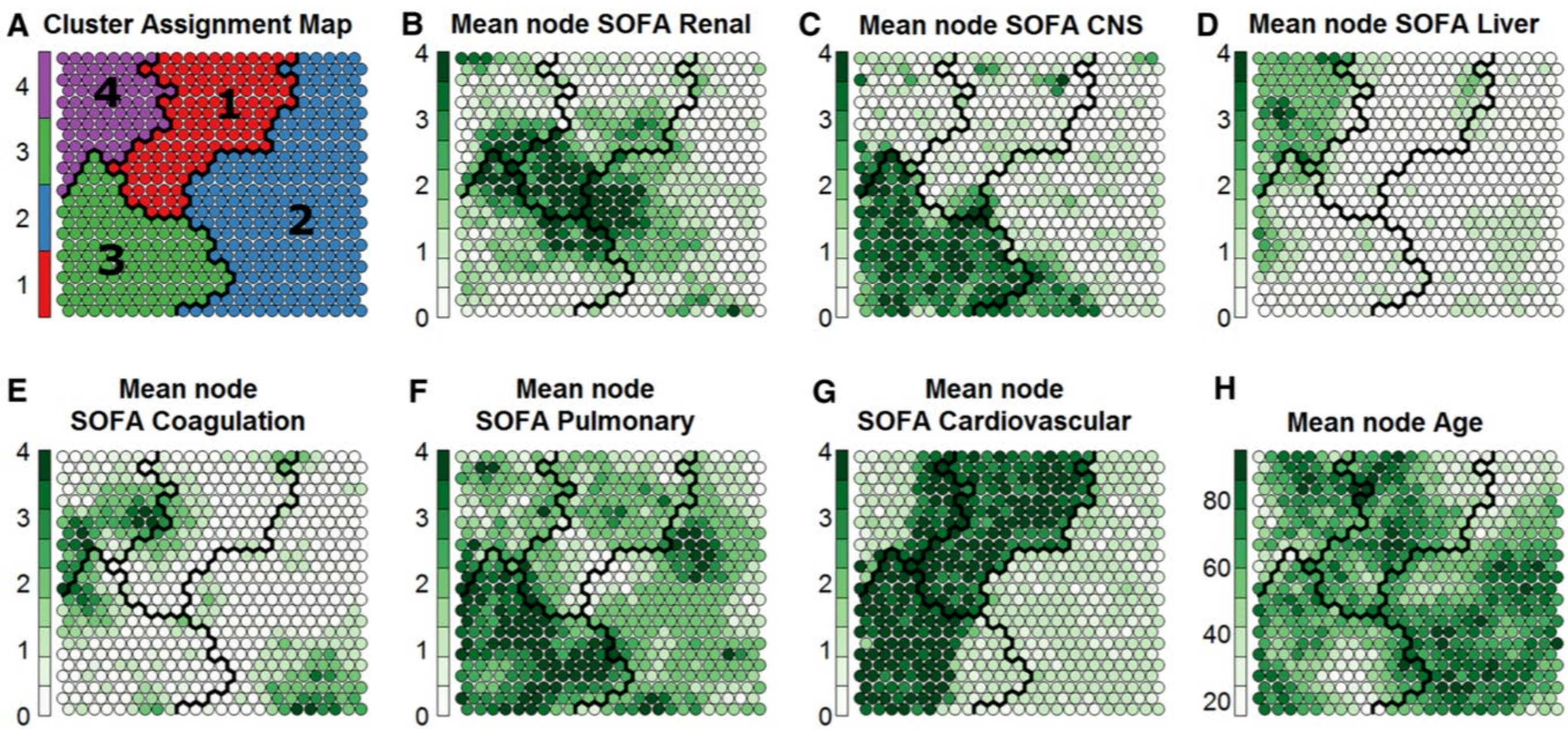
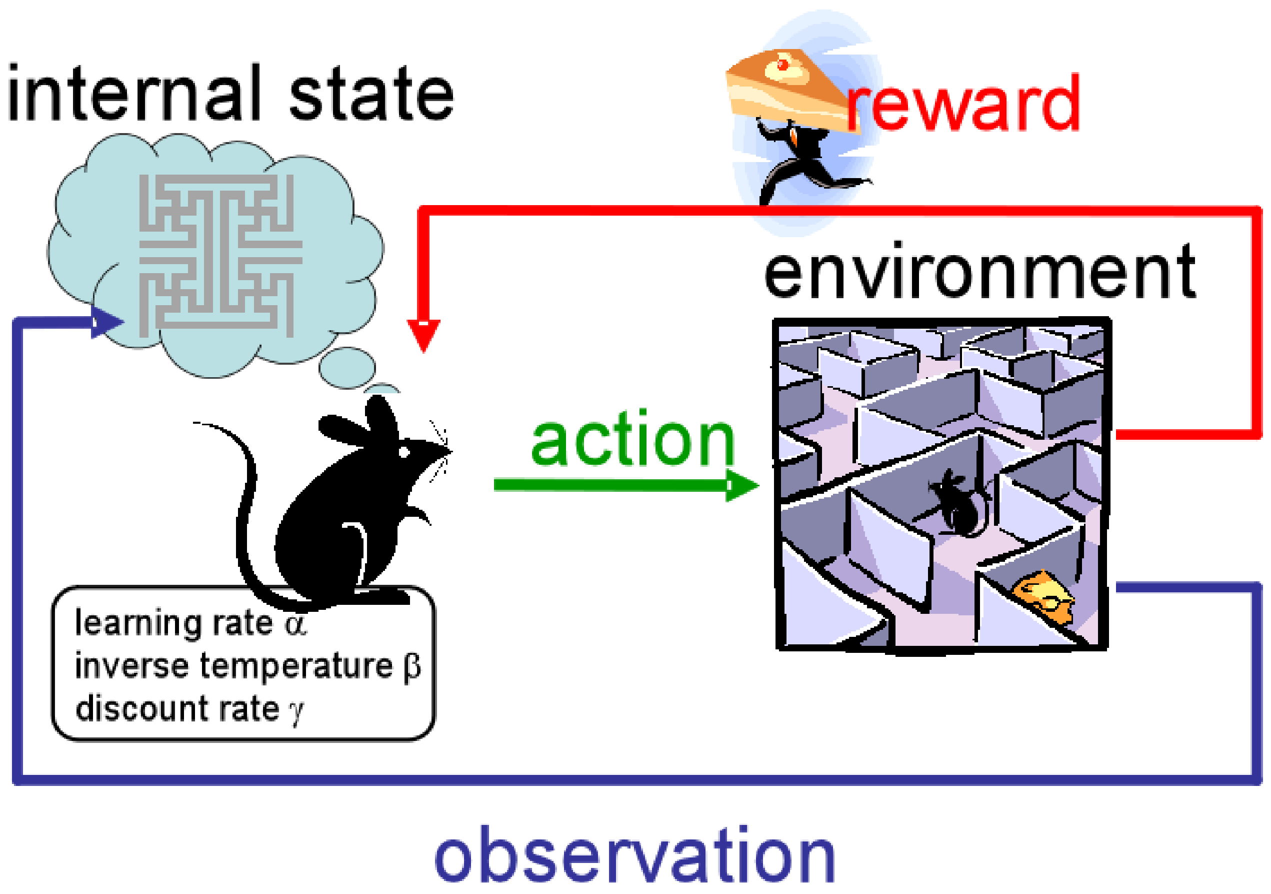



**Fig. 2** Kohonen Self-Organizing Maps. The maps depict both overall clusters and individual nodes (*circles*) to show the internal patterns within clusters. Nodes represent smaller groupings of patients: each node contains 0–20 patients who are extremely similar to each other. The four clusters are divided by *black lines* and depicted in (**a**). **b–f** Show those same clusters, but with depictions of different attributes of the nodes within each cluster. Within each node, the given value is represented by the darkness of the colour in the node. Each node is *shaded from white to dark green*, where darker colours represent higher average values (e.g., higher SOFA subscore) among the patients in the given node. The patterns visible in (**b–f**) suggest that the four clusters represent: *(1)* shock with elevated creatinine, *(2)* minimal multiple organ dysfunction syndrome, *(3)* shock with hypoxemia and altered mental status, and *(4)* hepatic disease

# Reinforcement learning



nature medicine
ARTICLES
https://doi.org/10.1038/s41591-018-0213-5

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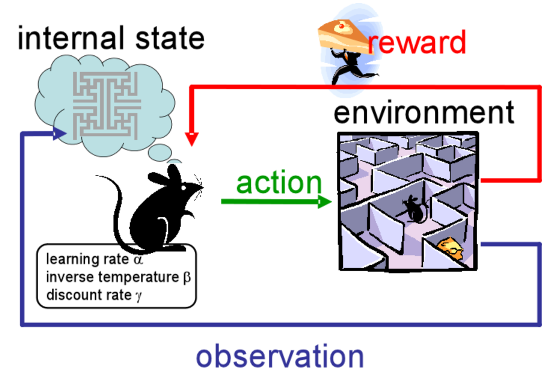
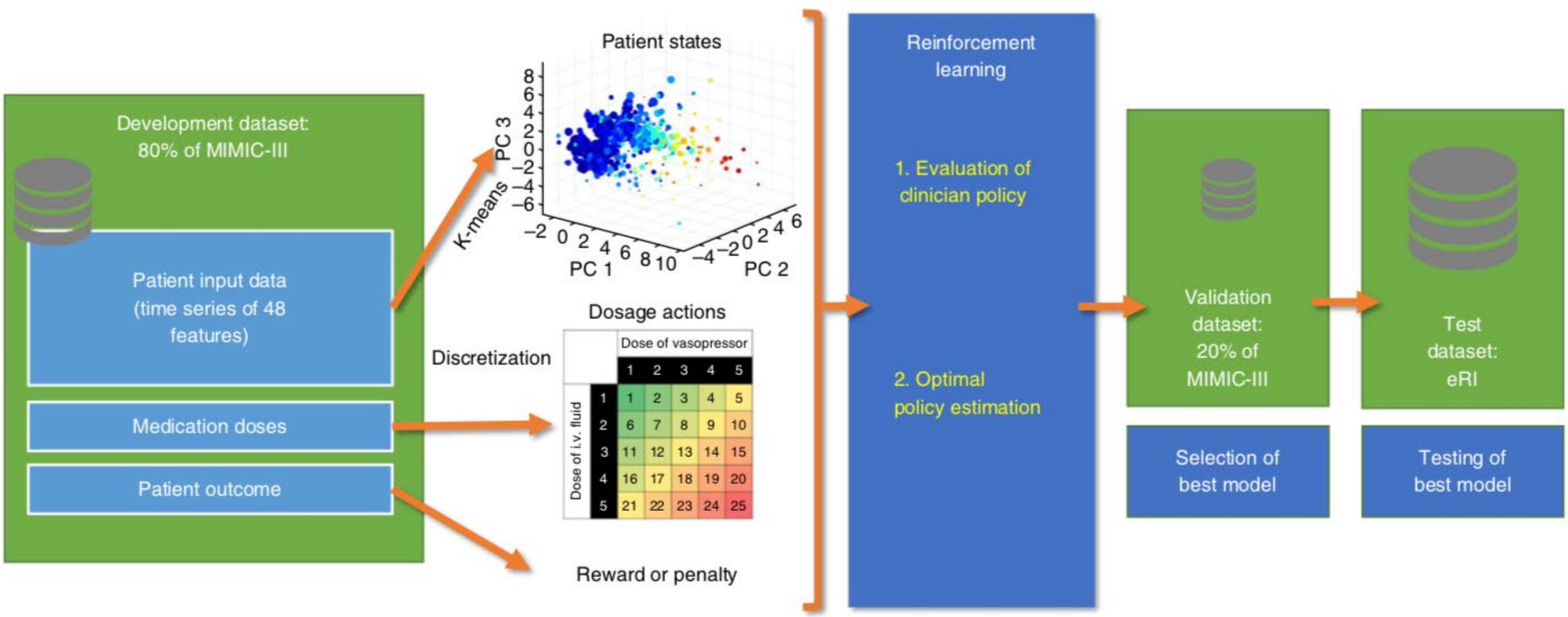
# The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care

Matthieu Komorowski[1,2,3], Leo A. Celi[3,4], Omar Badawi[3,5,6], Anthony C. Gordon[1*] and A. Aldo Faisal[2,7,8,9*]



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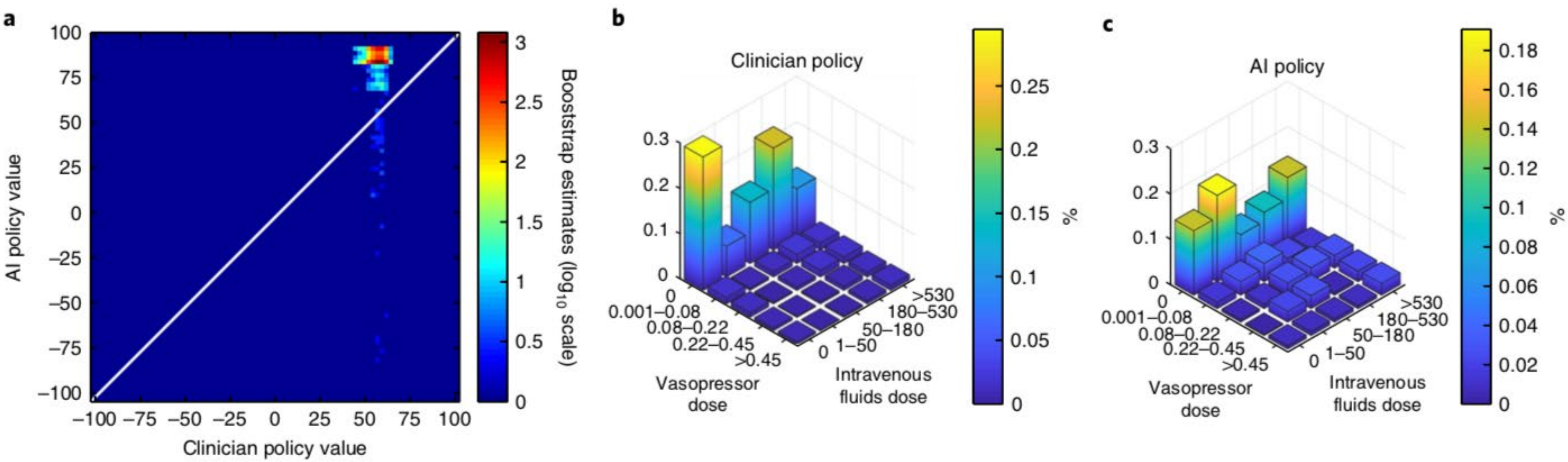

# Our main fears about AI

1. I do not understand AI!
2. AI will substitute me!
3. Who is responsible, if the AI result is wrong?

# Quintessence

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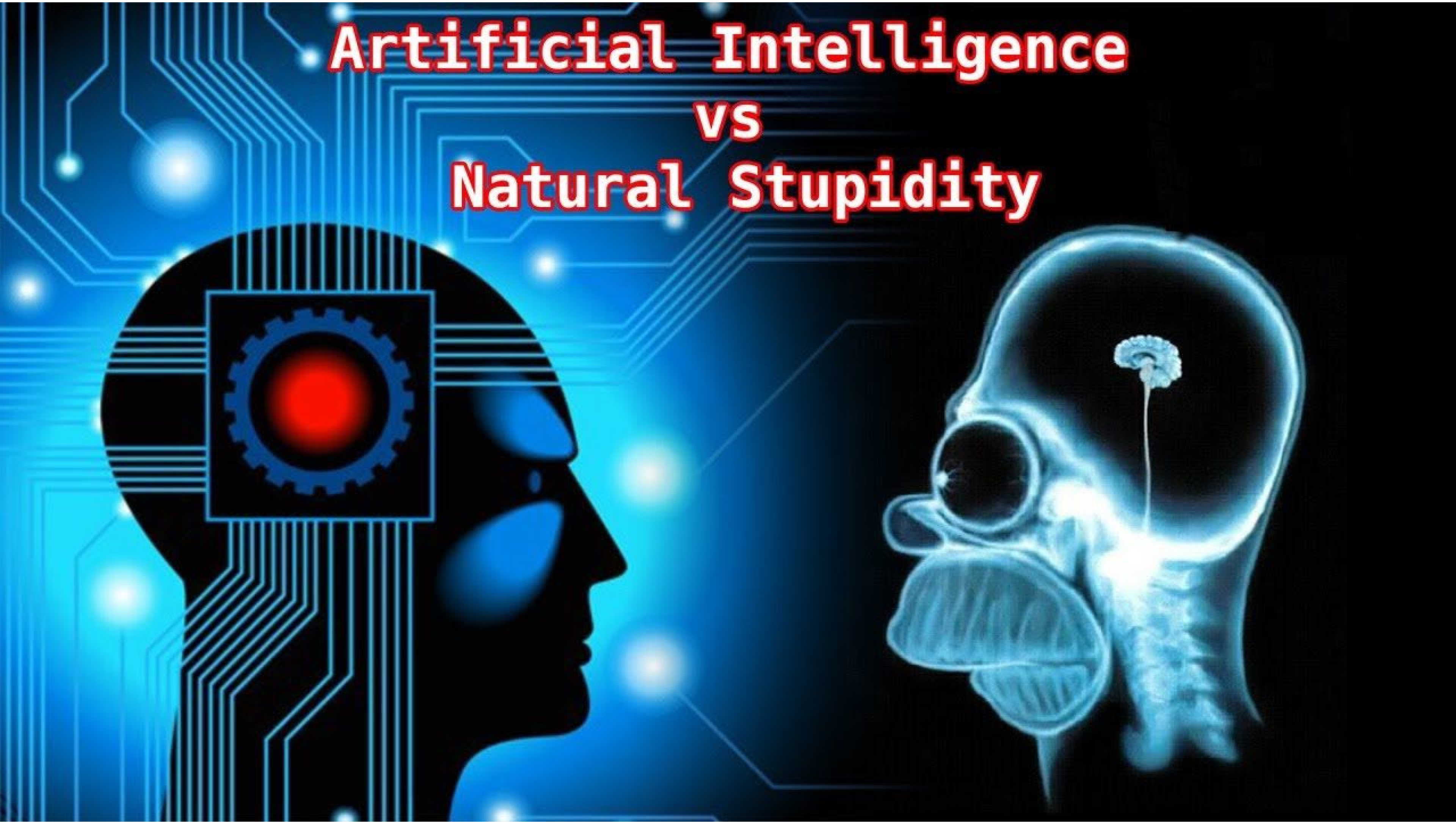
- There are three ML techniques that are widely used:

  Supervised, unsupervised and reinforcement learning

- They help for classification, clustering, and therapy recommendation

- Proof of concept, but still far away from daily clinical usage


Artificial Intelligence
vs
Natural Stupidity