What would other emergency stroke teams do?

Using explainable machine learning to understand variation in thrombolysis practice

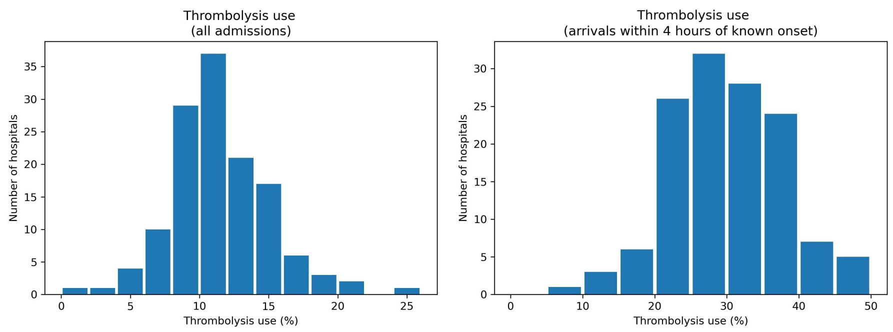
Kerry Pearn[1], Michael Allen[1,3], Anna Laws[1], Richard Everson[3], Martin James[1,2]

[1]University of Exeter Medical School [2]Royal Devon University Healthcare NHS Foundation Trust [3]University of Exeter Institute of Data Science and Artificial Intelligence

January 2023

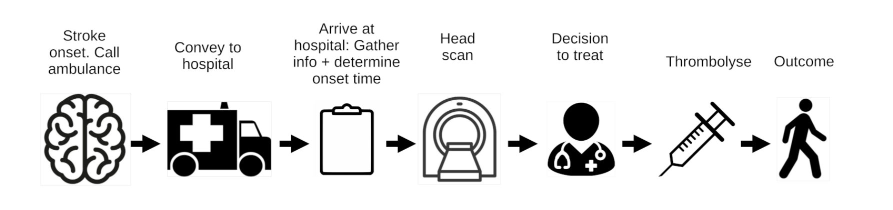
Thrombolysis rates vary .... a lot

Here we show the range of thrombolysis use across the 132 acute stroke centres in England and Wales. The NHS target is that 20% of patients should be receiving thrombolysis.



How much of this variation is due to differences in decisions hospitals make on who they would give thrombolysis to?

Breaking down the emergency stroke pathway into key steps

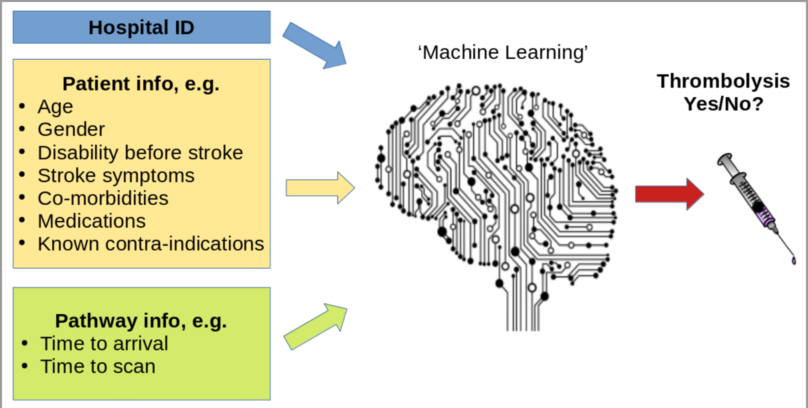


We can model key changes to pathway:

- What if the pathway were faster?
- What if hospital determined the stroke onset time in more patients?
- What if clinical decision-making was like that of *benchmark* hospitals? (Predict what treatment a patient would receive at other hospitals).

We model these changes with a hospital's own patient population, to allow for inter-hospital variation in patient population characteristics.

Machine learning overview

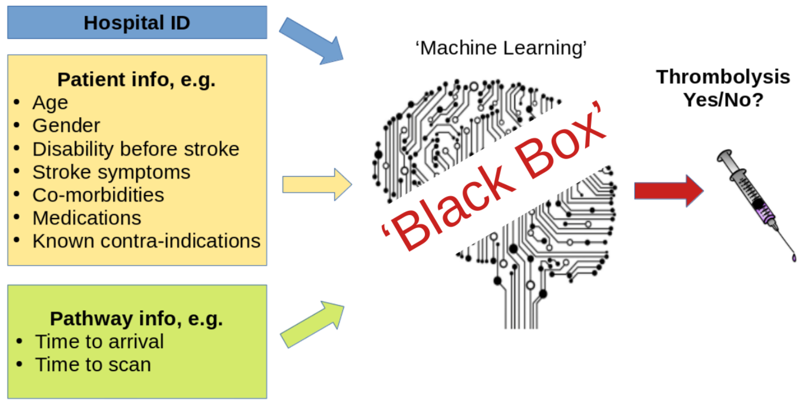


Machine learning (and nearly all *artificial intelligence*) is based on the simple principle of recognising similarity to what has been seen before.

We accessed 240,000 emergency stroke admissions in England and Wales over three years.

A *Black Box* model

When we don't know how a model is making predictions we call it a *Black Box* model.



Simplifying our model

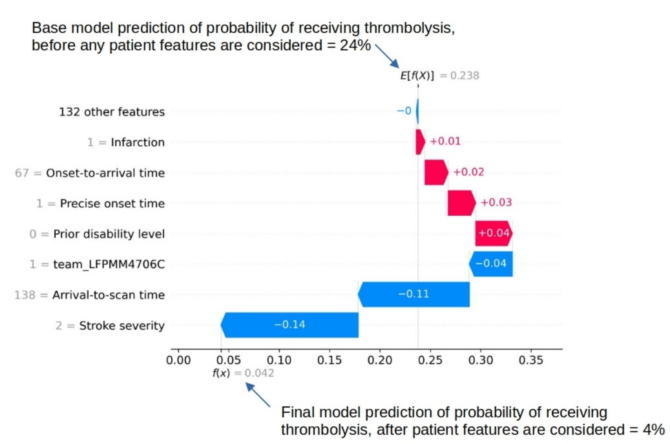
In order to simplify the model, to make it easier to explain, we reduced the number of patient features from 60 to 10, with almost no loss of model accuracy.

- *Arrival-to-scan time*: Time from arrival at hospital to scan (mins)
- *Infarction*: Stroke type (infarction or haemorrhage)
- *Stroke severity*: Stroke severity (NIHSS) on arrival (ranges from 0 to 42)
- *Precise onset time*: Onset time is known precisely
- *Prior disability level*: Disability level (modified Rankin Scale) before stroke
- *Stroke team*: Stroke team attended
- *Use of AF anticoagulants*: Use of atrial fibrillation anticoagulant
- *Onset-to-arrival time*: Time from onset of stroke to arrival at hospital
- *Onset during sleep*: Did stroke occur in sleep?
- *Age*: Age (as middle of 5 year age bands)

SHAP values - looking into the *Black Box*

SHAP (SHapley Additive exPlanations) values show us the contribution of each patient feature, even in a *Black Box* model.

These are found by running predictions lots of times with only part of the data for each patient available each time.



What general patterns did we see?

The model revealed that the odds of receiving thrombolysis:

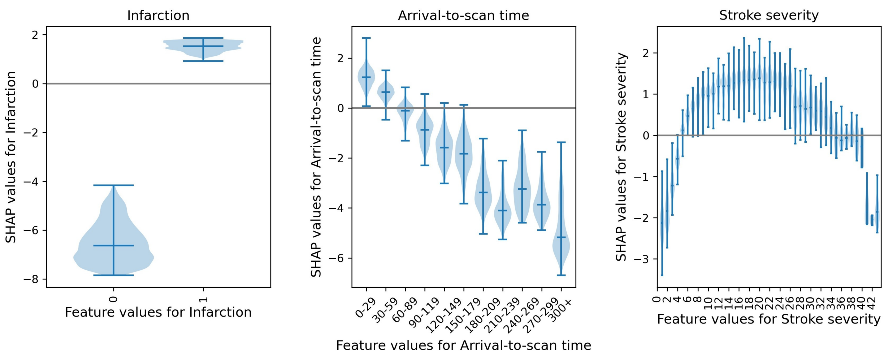
- Reduced 20 fold over the first 100 minutes of arrival-to-scan time
- Varied 30 fold depending on stroke severity, with lowest thrombolysis use at low or very high stroke severities
- Reduced 3 fold when the stroke onset time was not precisely known
- Fell 5 fold with increasing pre-stroke disability
- Varied 15 fold between hospitals

The majority of the variation in thrombolysis use between hospitals may be explained by differences in the hospitals' willingness to use the treatment, rather than the characteristics of the patients they treated.

Compared with hospitals with higher thrombolysis use, hospitals with lower use were particularly less likely to give thrombolysis to patients with milder strokes, prior disability, or patients with imprecise onset time.

Viewing the SHAP result - 1

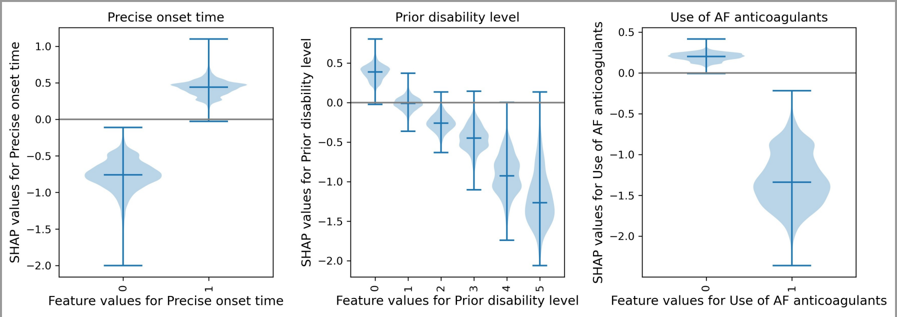
The previous observations on what affects the odds of receiving thrombolysis, came from these SHAP plots.



SHAP effects:
±1: Odds change ±3 fold
±2: Odds change ±7 fold
±3: Odds change ±20 fold
±4: Odds change ±55 fold
±5: Odds change ±150 fold

Viewing the SHAP result - 2

The previous observations on what affects the odds of receiving thrombolysis, came from these SHAP plots.



SHAP effects:
±1: Odds change ±3 fold
±2: Odds change ±7 fold
±3: Odds change ±20 fold
±4: Odds change ±55 fold
±5: Odds change ±150 fold

Artificial patients

We can *construct* artificial patients:

- Arrival-to-scan time = 15 minutes
- Stroke type = Infarction
- Stroke severity (NIHSS) = 15
- Precise onset time = Yes
- Prior disability level = None
- Use of AF anticoagulants = No
- Onset-to-arrival time = 60 minutes
- Onset during sleep = No
- Age = 72

99% hospitals would be expected to give this patient thrombolysis.

If we change stroke severity to mild (NIHSS), and make the stroke onset time not precise, 35% hospitals would be expected to give this patient thrombolysis.

Summary (generated by AI*)

This study used an explainable machine learning model to analyze data from 88,928 patients who arrived at emergency stroke units in England and Wales within 4 hours of known stroke onset.

The study found that there is substantial variation in the use of thrombolysis, a treatment for stroke, between hospitals, with rates ranging from 7% to 49%.

The study found that factors such as the amount of time between arrival at the hospital and being scanned, the severity of the stroke, the patient's pre-existing disability, and whether the stroke onset time was known precisely, influenced the odds of receiving thrombolysis.

However, the study found that the majority of the variation in thrombolysis use between hospitals may be explained by differences in the hospitals' willingness to use the treatment, rather than the characteristics of the patients they treated.

*Summary generated by ChatGPT (`https://openai.com/blog/chatgpt/`).