

Prediction of Disease Progression in Acute Liver Injury Patients Using Machine Learning and Mathematical Modeling

Raiki Yoshimura¹, and Shingo Iwami¹

¹Department of Biological Science, Graduate School of Science, Nagoya University

yoshimura.raiki21@gmail.com

iBLab

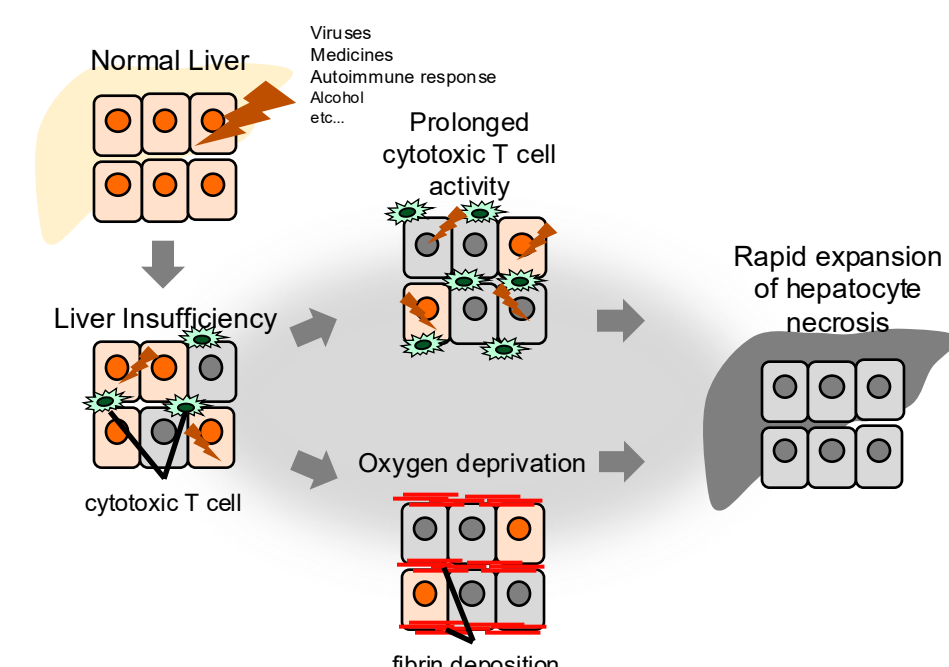


Abstract

- Acute liver failure (ALF) is so rare and serious disease.
- whose lifesaving rate heavily depends on physicians' experience and expertise.
- We found PT% as a biomarker that reflects the patient's condition from blood test data.
- We developed a quantitative model to predict future ALF conditions.

Introduction

Acute Liver Failure (ALF): rare and serious disease



Life-saving rates

Coma (Acute)	44%
Come (Sub-acute)	27%
LOHF (Late Onset Hepatic Failure)	3.6%

(2010-2014 in Japan)

S. Mochida, Journal of the Japanese Society of Internal Medicine, Vol. 105, No. 8

- ✓ ALF leads liver shutdown and death.
- ✓ A rare disease (about 400 cases a year).
- ✓ A serious disease (less than 50% lifesaving rates)

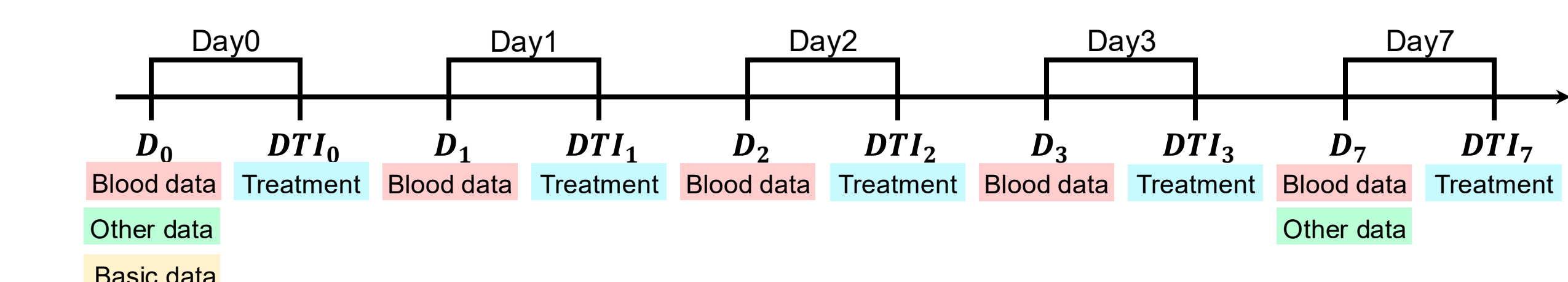
Lifesaving rates strongly depend on physician's expertise



- ✓ A physician has to decide on the treatment, especially the necessity of Liver transplantation (LT)

Results & Methods

Acute Liver Failure dataset from Kyushu University Hospital



Criteria: Acute Liver Injury(ALI)/ALF patients

- ALT more than 200 U/l
- T. Bil. more than 4 mg/dl
- PT-INR over 1.2 at admission

Basic data

- Sex
- Age

Other data

- Etiology
- Encephalopathy
- diagnosis

Treatment data

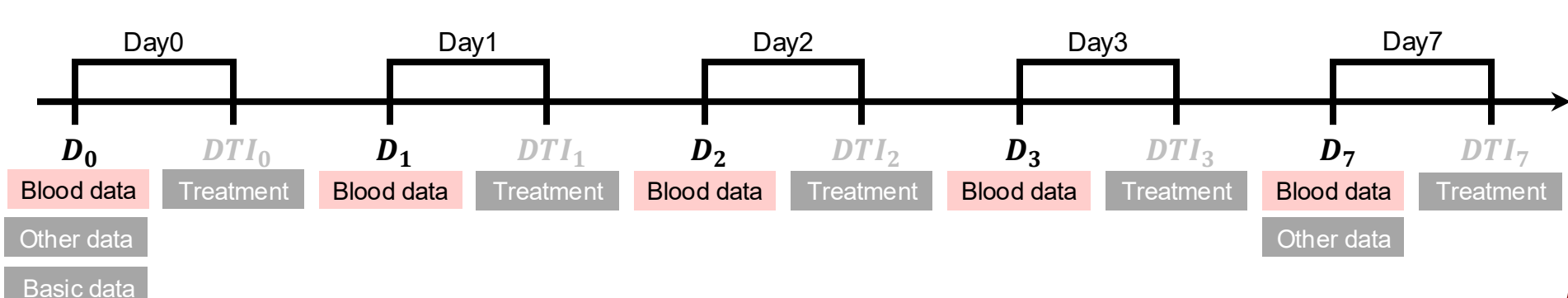
- FFP prescribing
- PE
- Steroid pulse therapy
- Anticoagulation
- CHDF
- Vasopressor Use

Blood test data

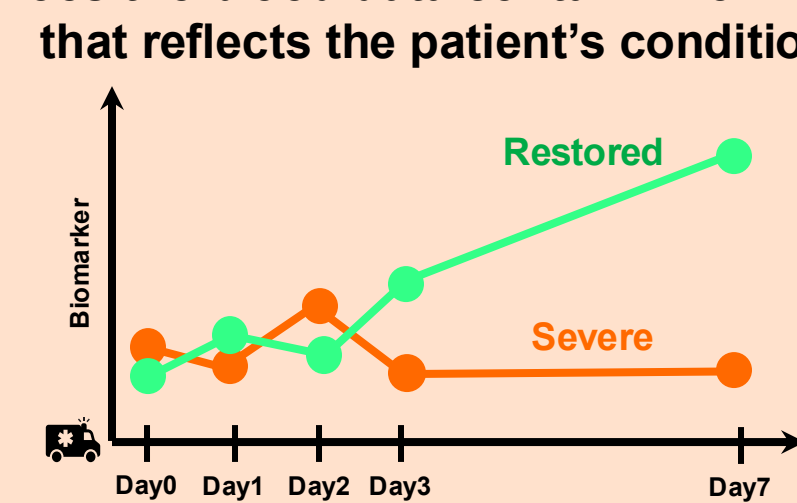
• WBC	• Ferritin
• Plt	• PTs
• Alb	• PT%
• Tbil	• PTINR
• Dbil	• APTT
• AST	• Fib
• ALT	• ATIII
• LDH	• IgG
• ALP	• IgA
• gGTP	• IgM
• Che	• AFP
• NH3	• PIVKA
• BUN	• sIL2R
• Cre	• D-bil/IT-bil
• CRP	• MELDscore

- ✓ Kyushu University has one of the biggest ALF cohorts in Japan.
- ✓ We utilized time-series blood test data until day 7 post-admission

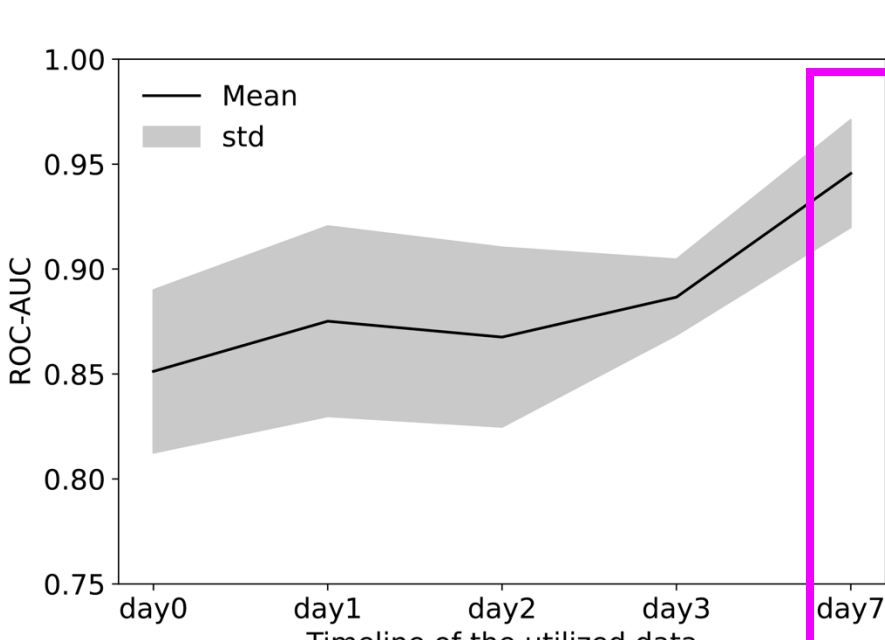
PT% as a biomarker that reflects patient's condition and relates to clinical outcomes (i.e., Liver Transplantation: LT)



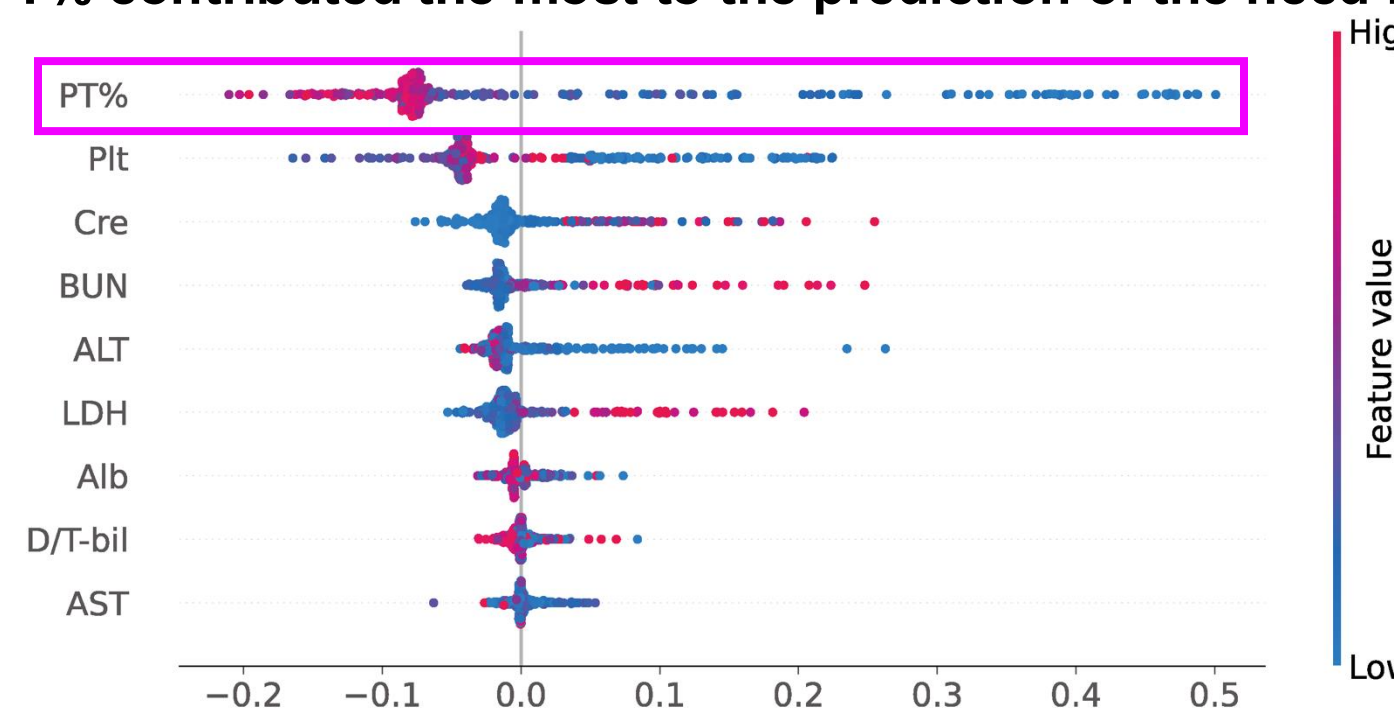
Does the blood data contain information that reflects the patient's condition?



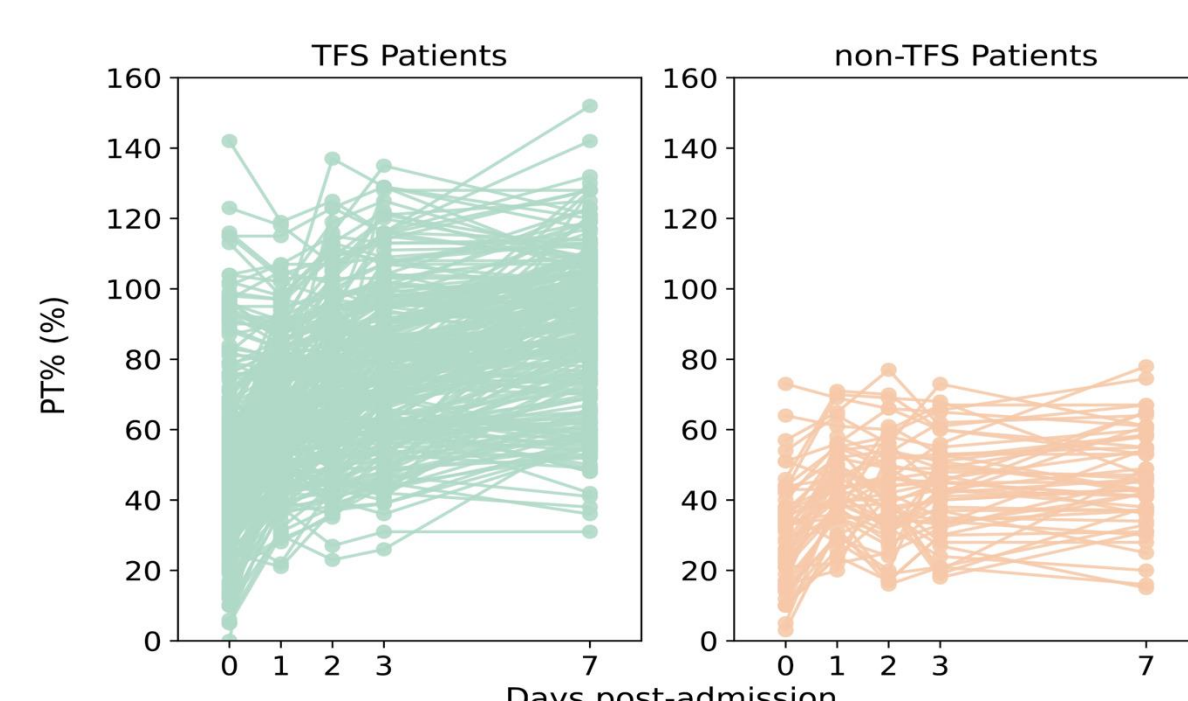
Random Forest Classifier for predicting the necessity of LT



PT% contributed the most to the prediction of the need for LT



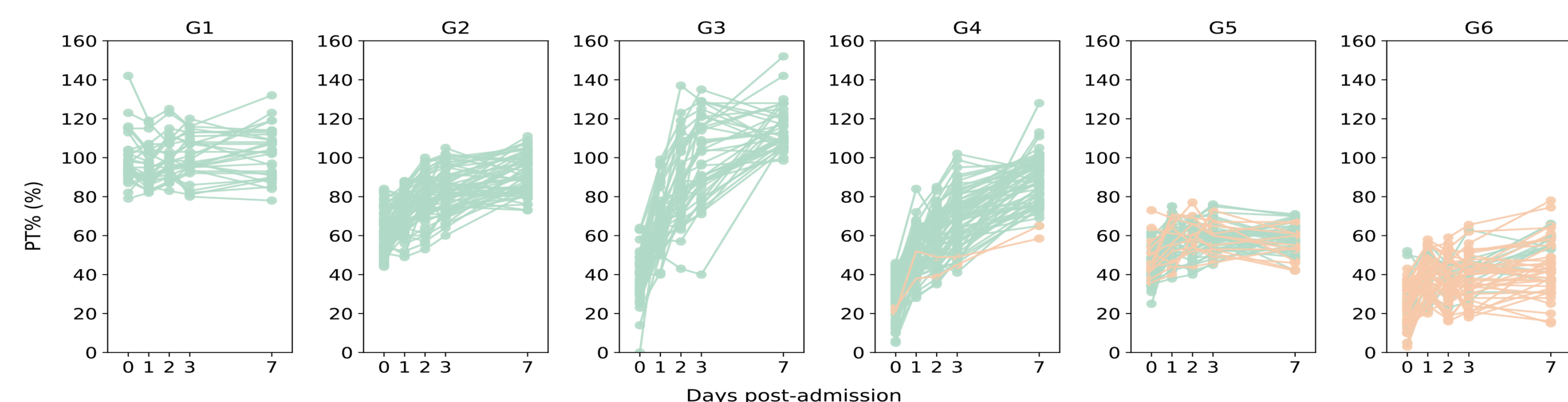
PT dynamics vary widely among individuals



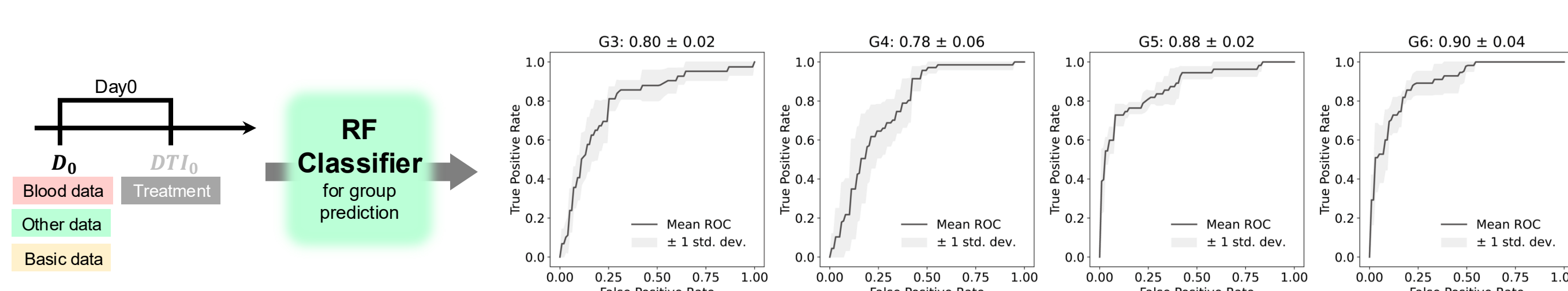
Results & Methods

Stratification and prediction in population-level

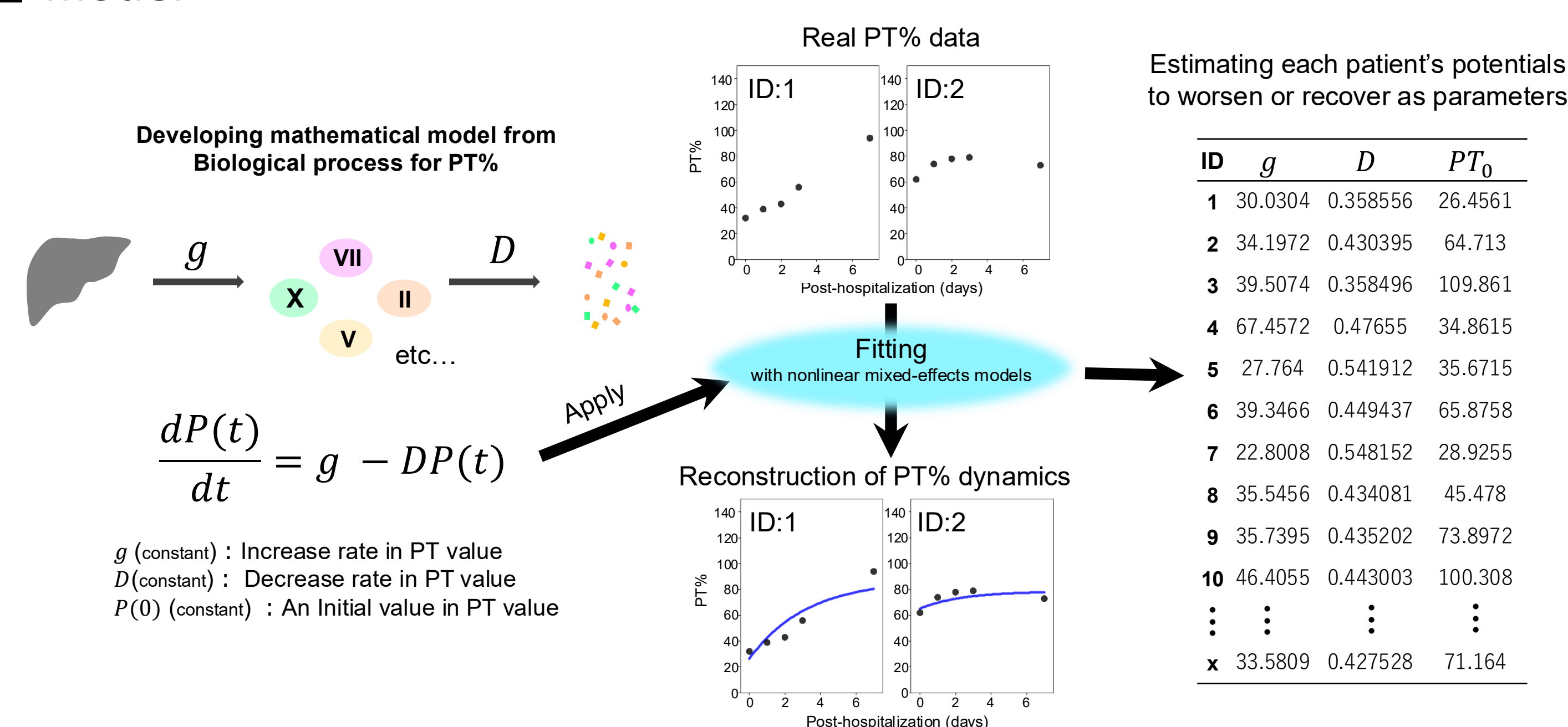
Clustering by dynamic time warping (DTW) using only PT dynamic information



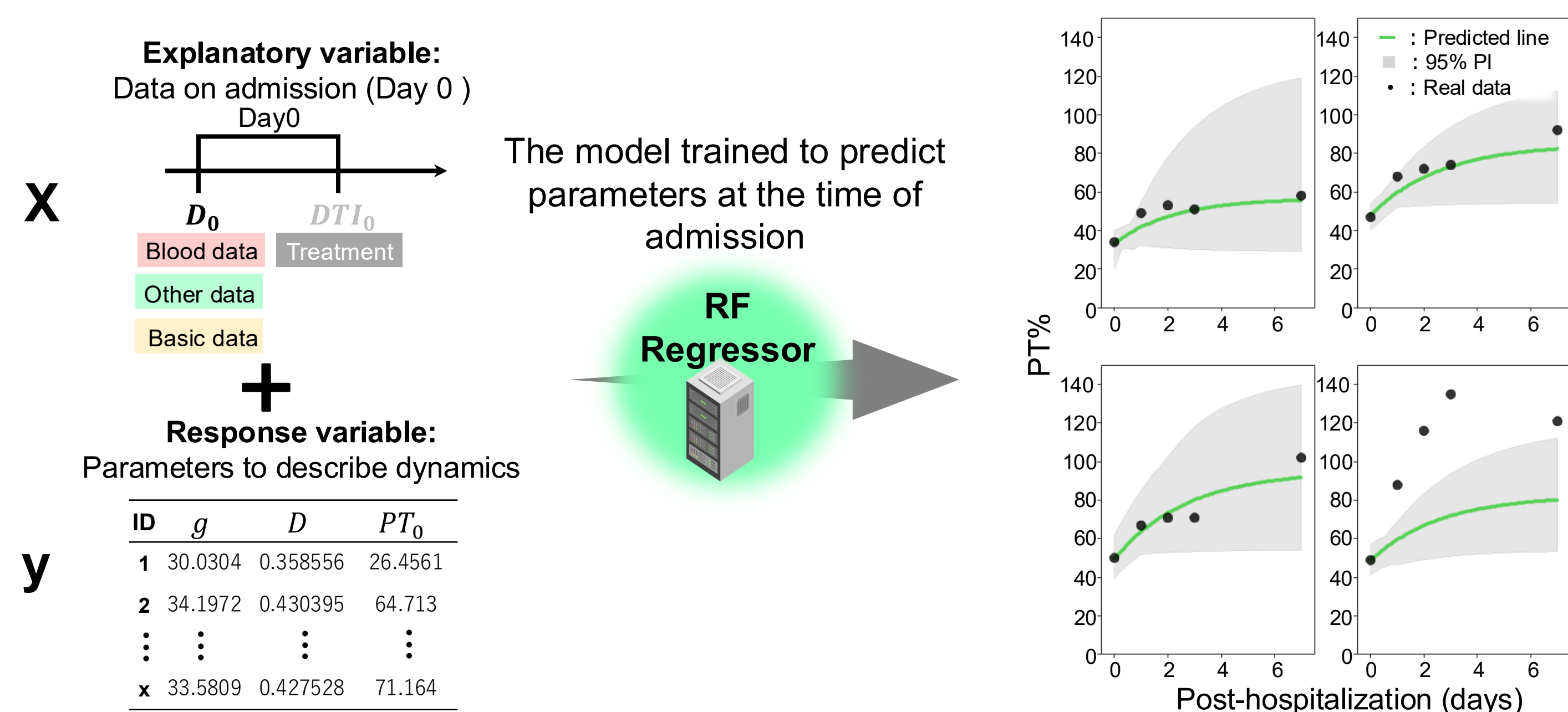
A binary classification model that predicts which group the patient could be in at the time of admission



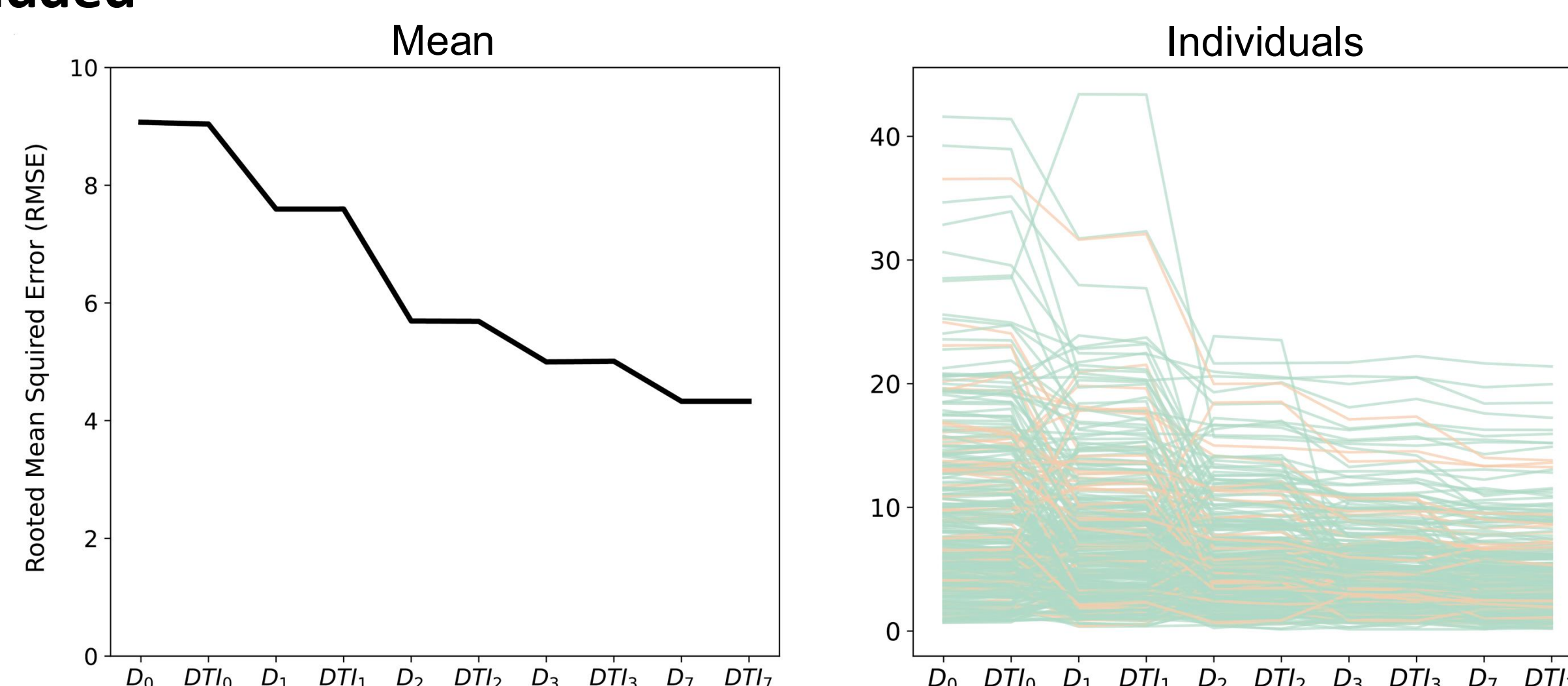
Reconstruction of individual-level PT% dynamics using mathematical model



PT% dynamics prediction at the time of admission



RMSE change in predicting performance when time series information is added



Conclusion

- PT% was quantitatively found as a biomarker that reflects the patient's condition
- Six groups of time-series change patterns in PT% are identified
- A mathematical model is developed to describe the dynamics of PT%
- A machine learning model was developed to predict PT% dynamics at the time of admission.
- Based on RMSE changes, we found that appropriate therapeutic intervention should be implemented by the second day.