

Yongjie YIN, Hui RUAN, Yang CHEN, Jiong CHEN, Ziyue LI, Xiang SU, Yipeng ZHOU, Qingyuan GONG, 2025. Prototypical clustered federated learning for heart rate prediction. *Frontiers of Information Technology & Electronic Engineering*, 26(10):1896-1912. <https://doi.org/10.1631/FITEE.2500062>

# Prototypical clustered federated learning for heart rate prediction

**Key words:** Federated learning; Heart rate prediction; Prototypical contrastive learning

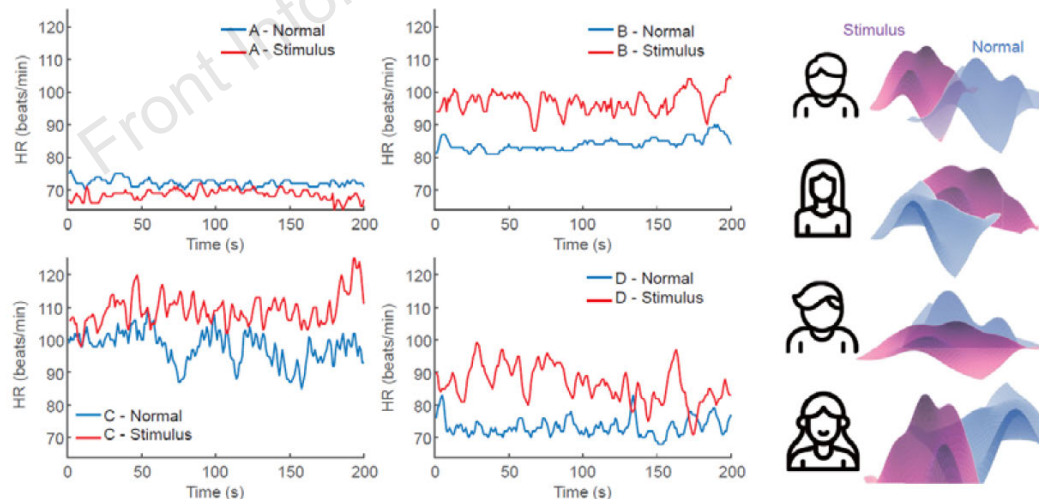
Corresponding author: Qingyuan GONG

E-mail: [gongqingyuan@fudan.edu.cn](mailto:gongqingyuan@fudan.edu.cn)

 ORCID: <https://orcid.org/0000-0001-7942-8752>

# Motivation

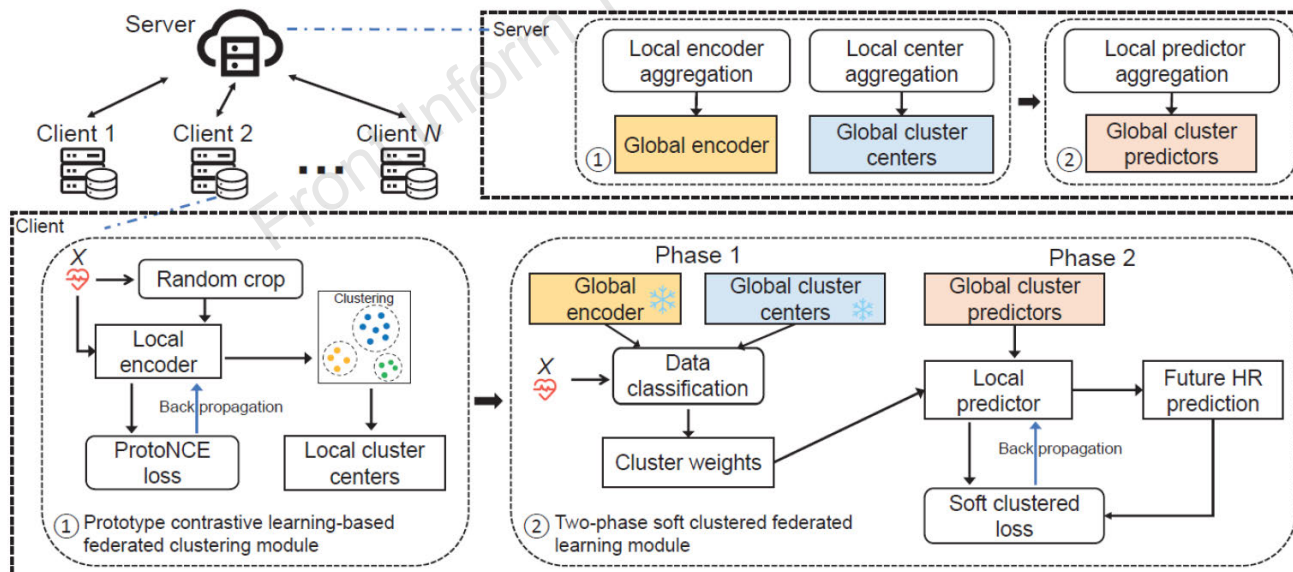
- ❑ **Privacy Risk of Heart Rate Prediction:** Centralized heart rate training exposes **sensitive physiological HR data**, compromising data privacy and highlighting the need for **federated learning (FL)**.
- ❑ **Data Heterogeneity and Client Disconnection:** Existing methods suffer performance degradation due to the **inherent heterogeneity of heart rate data** and **temporary client disconnections** to the central server.
- ❑ **Need for an Effective Methods:** There is an urgent demand for **robust and privacy-preserving** solutions to enhance personalized heart rate prediction.



Heart rate patterns of different individuals under varying conditions

# Method

- We propose a federated learning-based approach named **PCFedH**, which provides personalized and applicable heart rate prediction.
- The **prototypical contrastive learning-based federated clustering module** is designed to extract representations from heterogeneous heart rate data, achieving **privacy-preserving and accurate** clustering across clients.
- The **two-phase soft clustered federated learning module** trains personalized FL models for heart rate prediction, effectively mitigating data heterogeneity.



Architecture of the PCFedH model

# Major Results

## Prediction results

- PCFedH outperforms all the baselines, across both datasets, achieving average reductions of 3.1% in MSE, 1.6% in MAE, and 1.7% in MAPE compared with the second-best results.
- PCFedH can effectively recognize and use inter-client differences, enhancing the model's personalized adaptability.

Table 2 Performance comparison of PCFedH and baseline methods on the datasets of PPG-DaLiA and Distracted

Method	PPG-DaLiA			Distracted		
	MSE	MAE	MAPE (%)	MSE	MAE	MAPE (%)
FedAvg	2.621±2.060	1.121±0.398	1.445±0.583	20.242±153.889	1.466±4.076	1.486±1.804
FedProx	<u>2.597±1.784</u>	1.126±0.388	<u>1.441±0.553</u>	<u>1.665±1.209</u>	<u>0.929±0.393</u>	<u>1.202±0.519</u>
FedALA	2.615±2.029	1.121±0.396	1.445±0.581	46.470±13.783	6.610±0.898	8.819±2.525
IFCA	2.624±2.008	1.125±0.393	1.449±0.575	19.868±151.646	1.404±4.018	1.402±1.773
FedSoft	2.737±1.861	1.155±0.394	1.478±0.556	1.671±1.214	0.930±0.395	1.205±0.522
FedCE	2.610±1.987	<u>1.121±0.391</u>	1.443±0.573	18.649±140.433	1.473±3.870	1.532±1.716
FedProto	23.133±19.097	3.559±1.552	4.445±1.658	99.373±450.702	4.503±7.050	4.715±3.565
FedPCL	11.239±24.140	2.410±2.330	3.028±2.996	38.898±244.490	3.532±5.141	4.144±3.996
PCFedH	<b>2.549±1.736</b>	<b>1.117±0.383</b>	<b>1.431±0.549</b>	<b>1.593±1.175</b>	<b>0.903±0.398</b>	<b>1.170±0.526</b>

MAE: mean absolute error; MAPE: mean absolute percentage error; MSE: mean squared error. The best result is highlighted in boldface, and the second-best result is underlined. It shows PCFedH's superior results in reducing MSE, MAE, and MAPE on the PPG-DaLiA and Distracted datasets

# Major Results

## Ablation study

- All modules in our model contribute to improving the performance of heart rate prediction.
- The marked decline after removing the soft clustered FL module suggests that different data types still mutually benefit each other, highlighting the necessity of soft clustering.

Table 3 Ablation study: SoftCluster is the most important design

Method	MSE	MAE	MAPE (%)
PCFedH (w/o PCL)	<u>2.553±1.729</u>	<u>1.118±0.381</u>	<b>1.431±0.542</b>
PCFedH (w/o CRE)	2.565±1.762	1.119±0.381	1.432±0.543
PCFedH (w/o DCP)	2.737±1.861	1.155±0.394	1.478±0.556
PCFedH (w/o SC)	2.785±1.957	1.165±0.379	1.490±0.546
PCFedH	<b>2.549±1.736</b>	<b>1.117±0.383</b>	<u>1.431±0.549</u>

MAE: mean absolute error; MAPE: mean absolute percentage error; MSE: mean squared error; w/o: without; PCL: prototypical contrastive learning; CRE: cluster representation encoder; DCP: data classification phase; SC: soft clustered. The best result is highlighted in boldface, and the second-best result is underlined

# Major Results

## Hyperparameter sensitivity analysis

- When the learning round  $R_{\text{pcl}}$  is set to 10 in the two-phase soft clustered FL module, PCFedH achieves satisfactory performance, maintaining efficiency without significant sacrifice in accuracy.

Table 4 Performance of PCFedH at varying PCL rounds

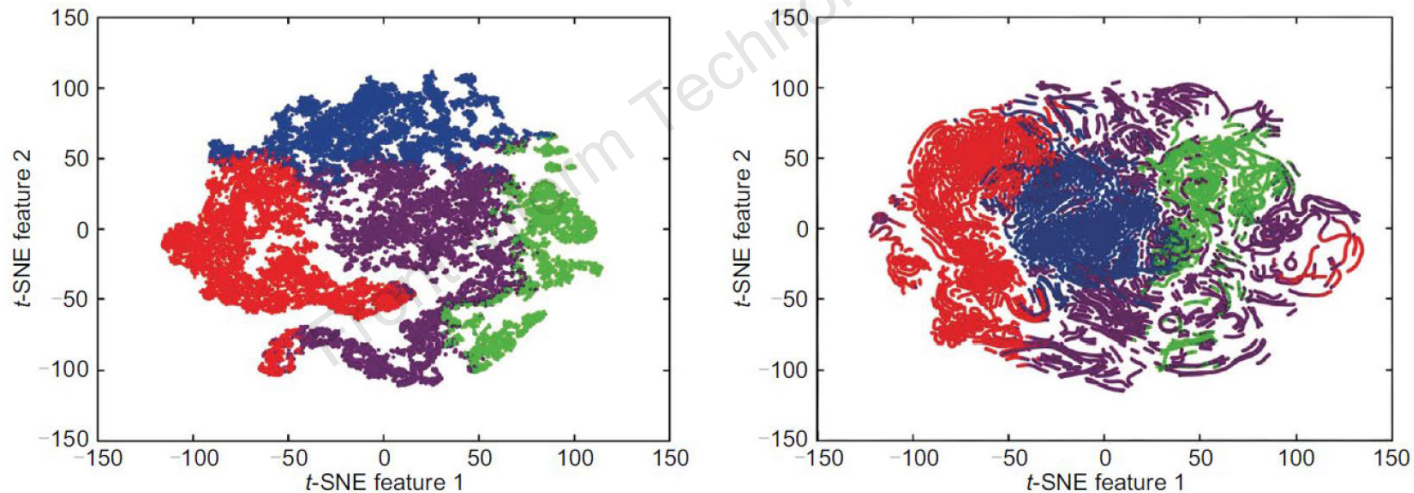
Round	MSE	MAE	MAPE (%)
$R_{\text{pcl}} = 1$	2.562±1.730	1.122±0.385	1.437±0.552
$R_{\text{pcl}} = 5$	2.548±1.745	1.119±0.389	1.433±0.560
$R_{\text{pcl}} = 10$	2.549±1.736	1.117±0.383	1.431±0.549
$R_{\text{pcl}} = 50$	2.565±1.762	1.118±0.381	1.430±0.542
$R_{\text{pcl}} = 100$	2.549±1.740	1.116±0.381	1.428±0.544

MAE: mean absolute error; MAPE: mean absolute percentage error; MSE: mean squared error; PCL: prototypical contrastive learning

# Major Results

## Visualization results

- The application of prototypical cluster learning significantly improves cluster separability, as illustrated by the  $t$ -SNE visualization after dimensionality reduction.



Visualizations of PPG-DaLiA dataset representations

Left: the enhanced representation by PCFedH; Right: the original representation

# Conclusions

---

- We propose PCFedH, a novel federated learning framework that addresses privacy concerns and handles the heterogeneity of heart rate data to achieve personalized and accurate heart rate prediction.
- By combining prototypical contrastive learning with clustered FL, PCFedH enhances clustering stability and improves model personalization under heterogeneous data distributions.
- Extensive experiments show a 3.1% reduction in MSE compared to suboptimal results, demonstrating significant improvement over state-of-the-art methods.

# Author Biography

---



**Yongjie YIN** received the B.S. degree from the Faculty of Information, Liaoning University, China, in 2024. He is currently pursuing the M.S. degree in the School of Computer Science, Fudan University, China. His main research interests include federated learning, social network analysis, and LLM-based agents.



**Qingyuan GONG** is currently a tenure-track Associate Professor at the Research Institute of Intelligent Complex Systems, Fudan University. She received her Ph.D. degree in Computer Science from the School of Computer Science, Fudan University, China, in 2020. Her research interests include network security, user behavior analysis, and computational social systems.