

BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics

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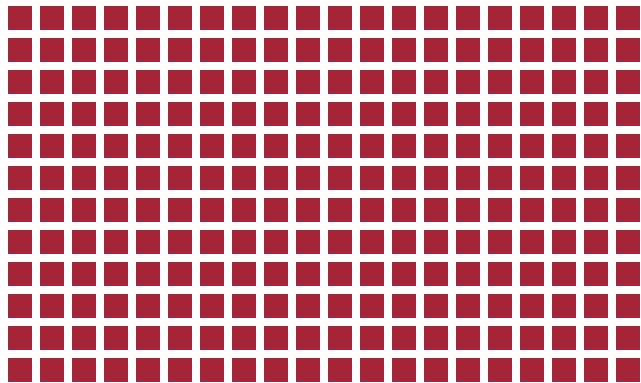
The Global Burden of Breast Cancer

2024 Global Estimates

2.4 Million

Women diagnosed

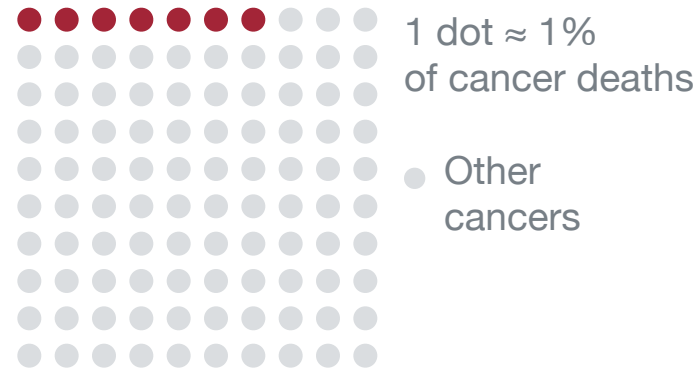
■ 1 square = 10,000 people



694,000

Breast cancer deaths

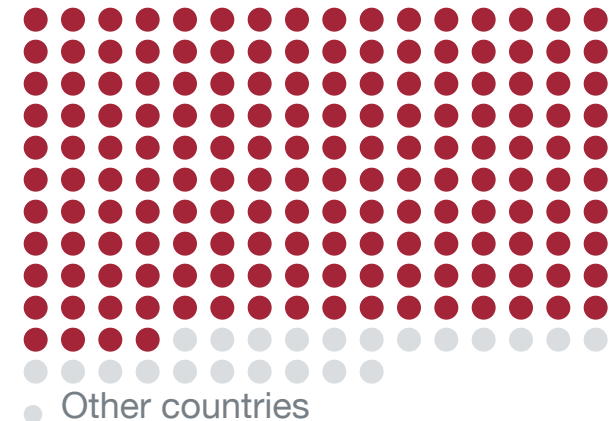
≈7% of all cancer deaths



164 of 186

Most common cancer
in women

● 1 dot = 1 country



[1] World Health Organization, "Breast cancer," Jul. 3, 2026.

[2] World Health Organization, "Cancer," Jul. 3, 2026.

Radiogenomics for Breast Cancer

What It Is

Links imaging phenotypes with gene expression and other molecular characteristics

Role in Breast Cancer

Noninvasive tumor characterization
Molecular subtype prediction

Toward More Personalized Care

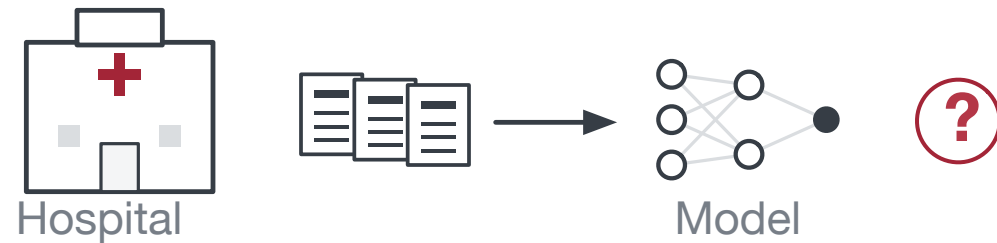
Imaging biomarkers may inform clinical decisions

[3] H. Li et al., "Quantitative MRI radiomics in the prediction of molecular classifications of breast cancer subtypes in the TCGA/TCIA data set," *npj Breast Cancer*, 2016.

[4] A. Y. Park et al., "MRI-based breast cancer radiogenomics using RNA profiling: association with subtypes in a single-center prospective study," *Breast Cancer Res.*, 2023.

Challenges in Clinical Model Training

1 Limited Local Data



Local data may be insufficient.

2 Local Data Only



Privacy keeps patient data local.

3 Continual Data Arrival



Incoming data requires continual updates.

4 Unavailable Past Data



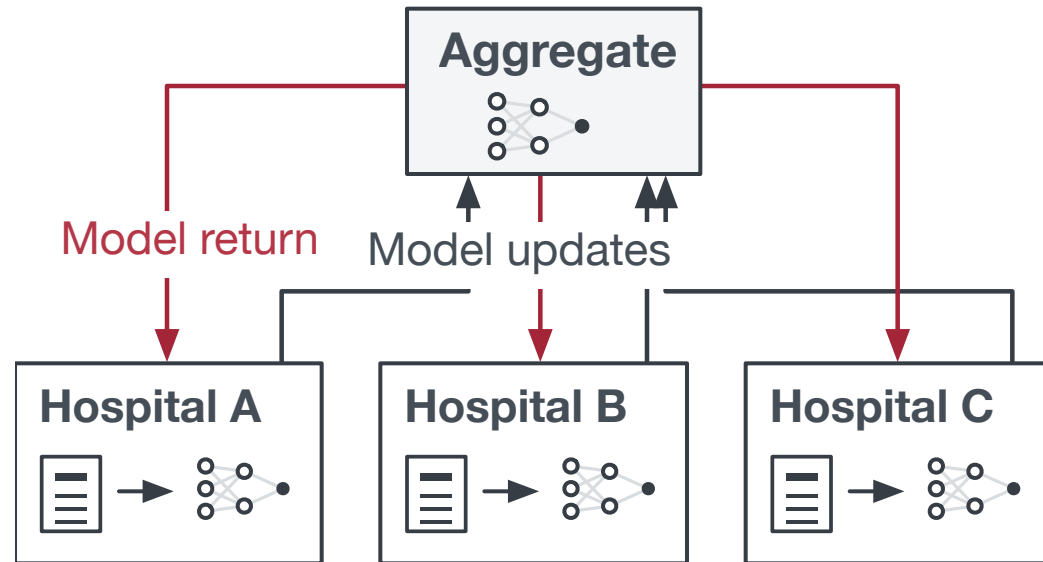
Storage and privacy restrict past data.

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

Federated and Continual Learning

Federated Learning (FL)

1 Learn Across Hospitals

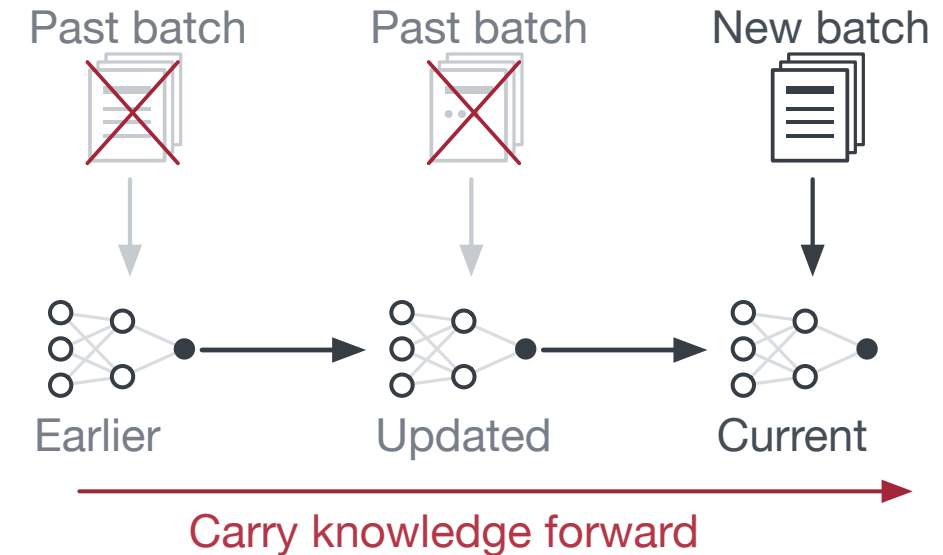


2 Keep Raw Data Local

Patient records stay at each hospital.

Continual Learning (CL)

3 Adapt to New Data



4 Retain Earlier Knowledge

Reduce forgetting without old raw data.

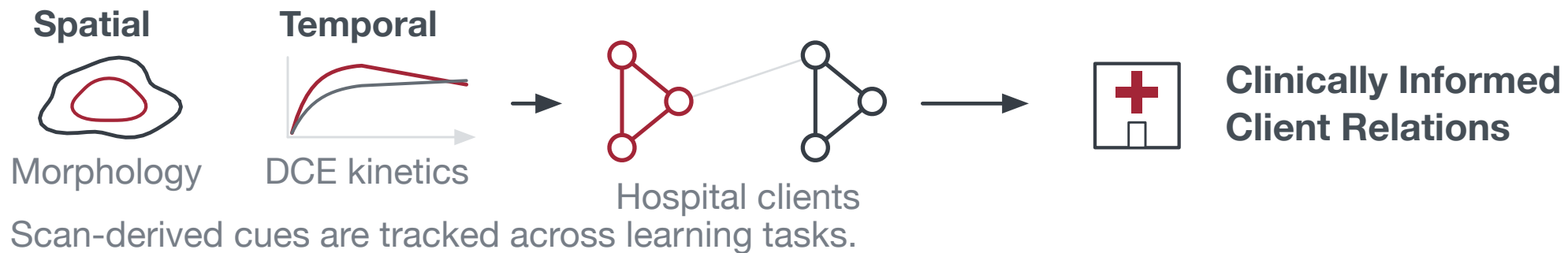
Generic Relations Miss Disease-Specific Cues

Existing Graph-Based FCL

e.g., GFedCL: updates + attention changes across learning tasks



BreastG-FCL



[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

Spatial Cues: Disease-Relevant Regions

1 Standardize MRI

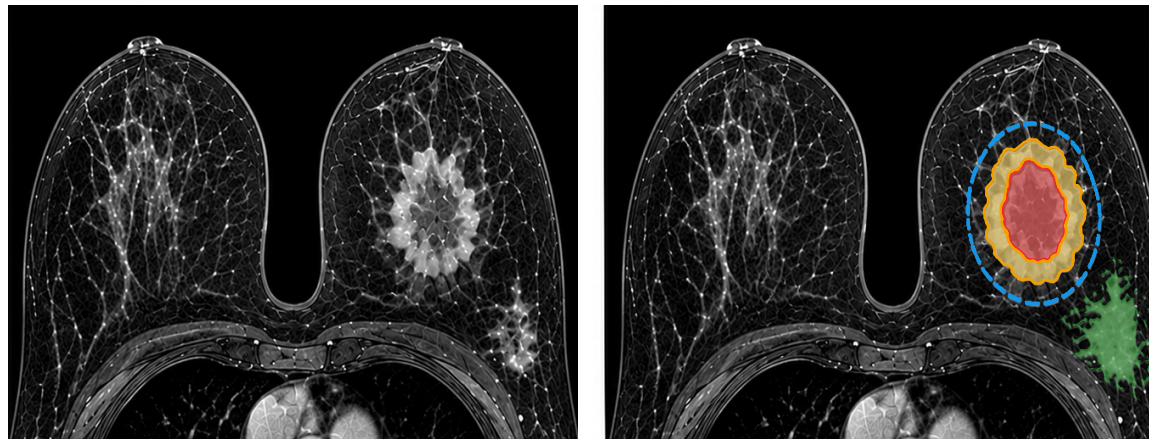
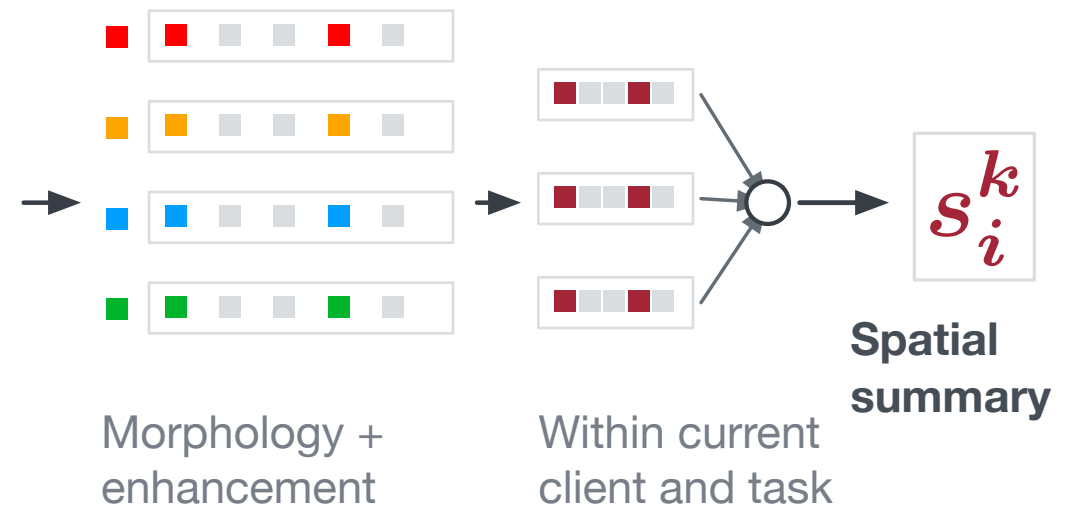
➔ 2 Segment Regions

3 Extract Features

4 Aggregate Features

 Tumor Core
 Peritumoral Ring

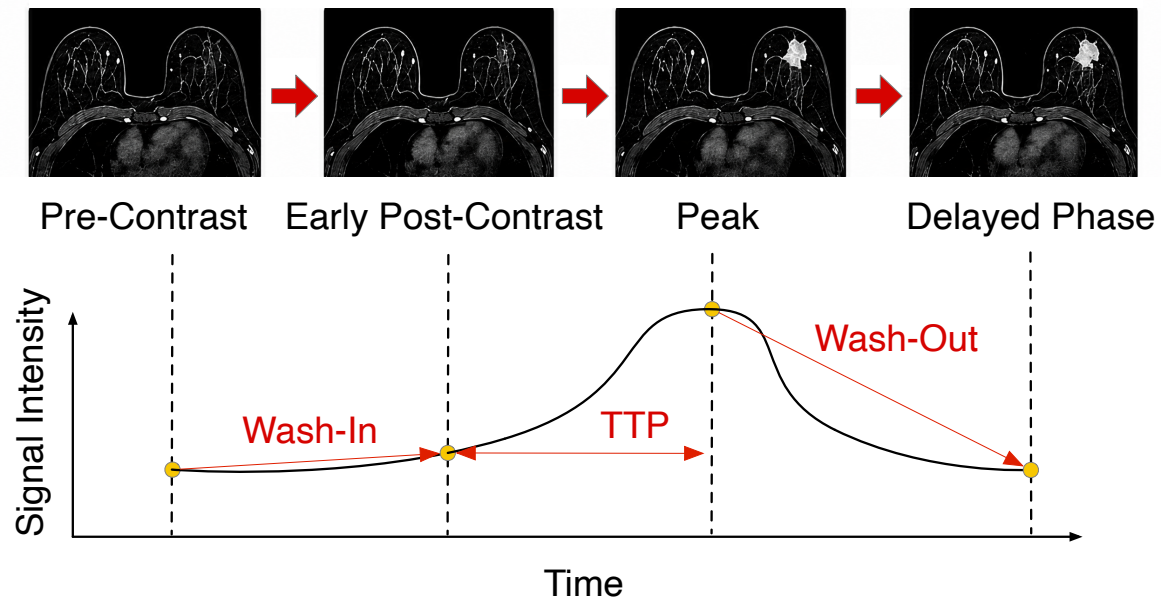
 Enhancing Rim
 BPE



BPE: background parenchymal enhancement.

Temporal Cues: DCE-MRI Enhancement Kinetics

1 DCE Sequence



2 Normalize

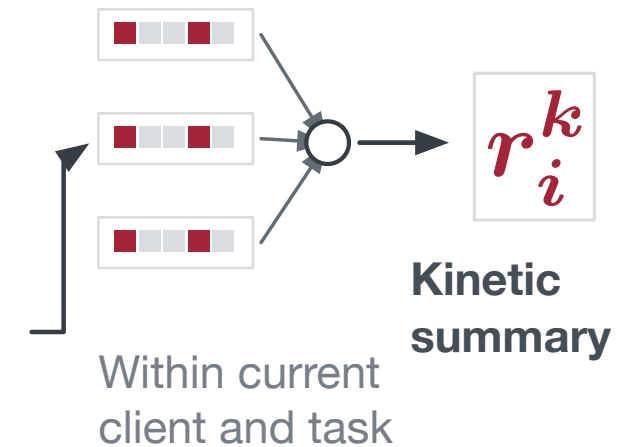
Enhancement



3 Extract Kinetics

Wash-in
Wash-out
Time-to-peak
SER

4 Aggregate



DCE phases occur within one scan. Summaries are tracked across learning tasks.

BreastG-FCL Overview

1 Construct disease-aware client relations

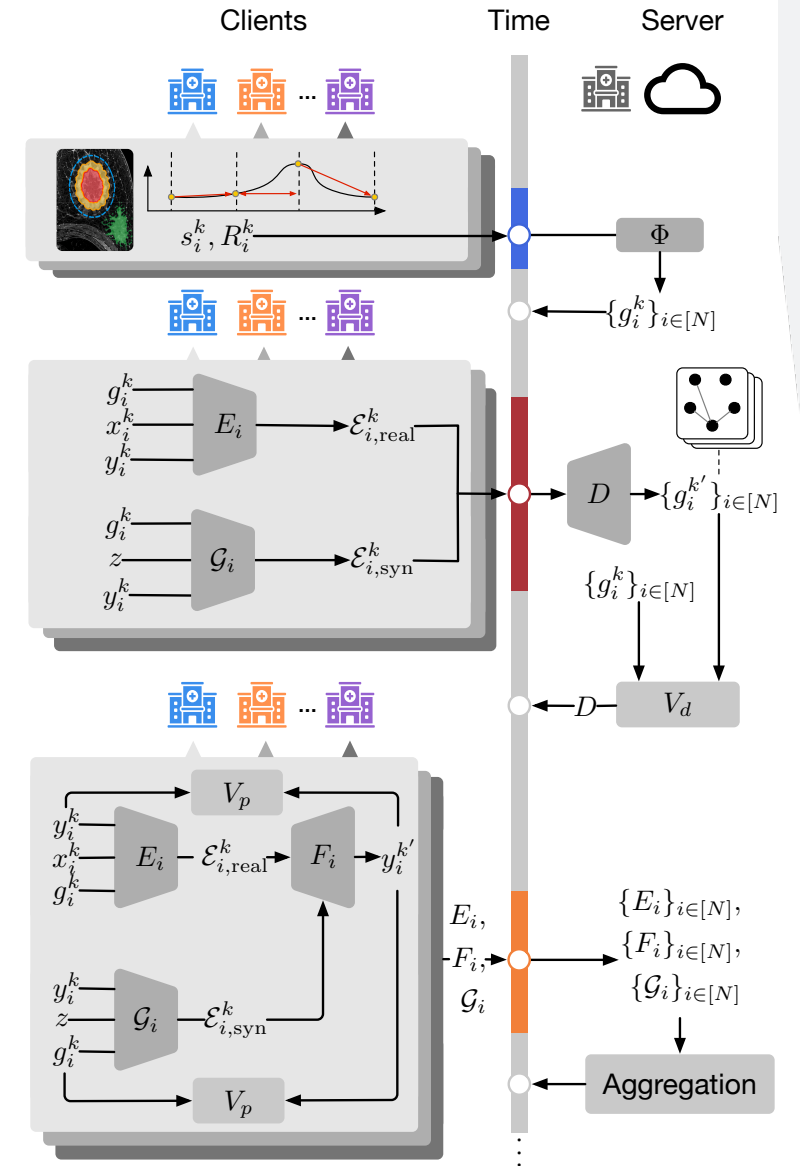
Morphology and kinetic summaries define a graph.

2 Align representations across clients

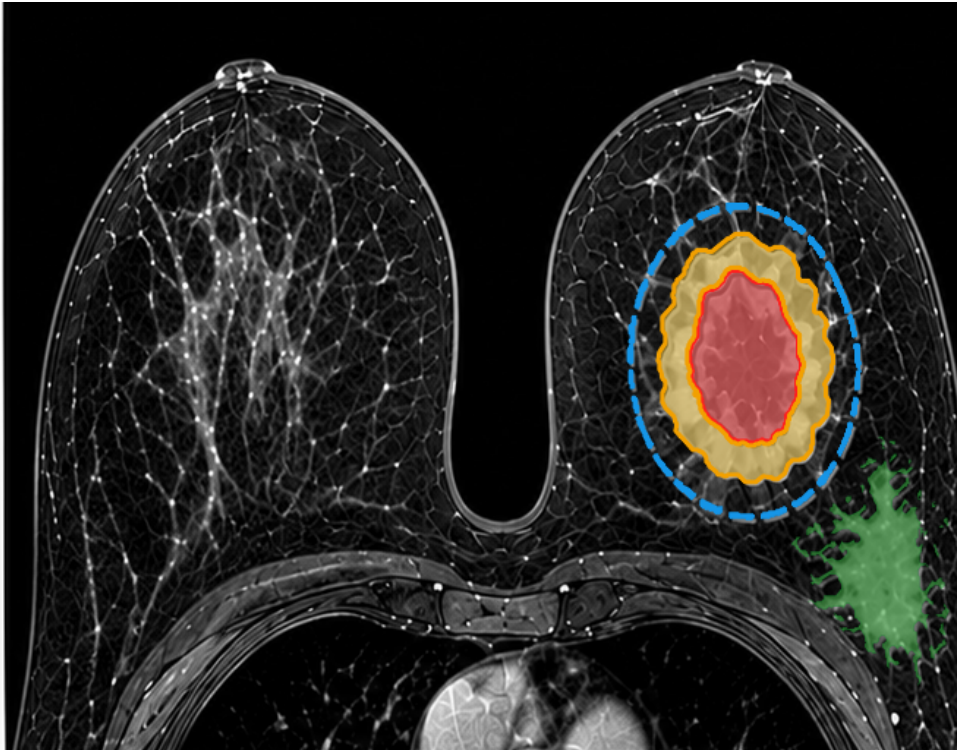
A shared discriminator provides the alignment signal.

3 Replay graph-conditioned representations

Current and historical relations guide latent replay.



Spatial Attention Compares Tumor Morphology



Per-client morphology summary

Aggregate regional descriptors
for the current task

Spatial attention

$$\alpha_{ij}^k = \text{softmax}_j(a_{\theta_s}(s_i^k, s_j^k))$$

Higher relevance for clients
with similar tumor morphology

Attention normalizes similarity over candidate clients.

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

Temporal Attention Follows Recent Kinetics

Recent kinetic history

$$R_i^k = \left[r_i^{\max(1, k-m+1)} \parallel \dots \parallel r_i^k \right]$$

Recent history

A sliding window retains recent task summaries.

Temporal attention

$$\beta_{ij}^k = \text{softmax}_j(b_{\theta_t}(R_i^k, R_j^k, m))$$

Compare enhancement histories across clients.

The window limits the influence of outdated tasks and controls representation size.

[5] Q. Yu et al., “BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics,” *IEEE HealthCom*, 2026.

Graph Fusion Requires Agreement in Both Cues

Spatial attention

Tumor morphology

Temporal attention

Enhancement dynamics

$$G_{ij}^k \propto \alpha_{ij}^k \times \beta_{ij}^k$$

Multiply the two attention scores, then normalize each graph row.

A strong edge needs support from both clinical signals.

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

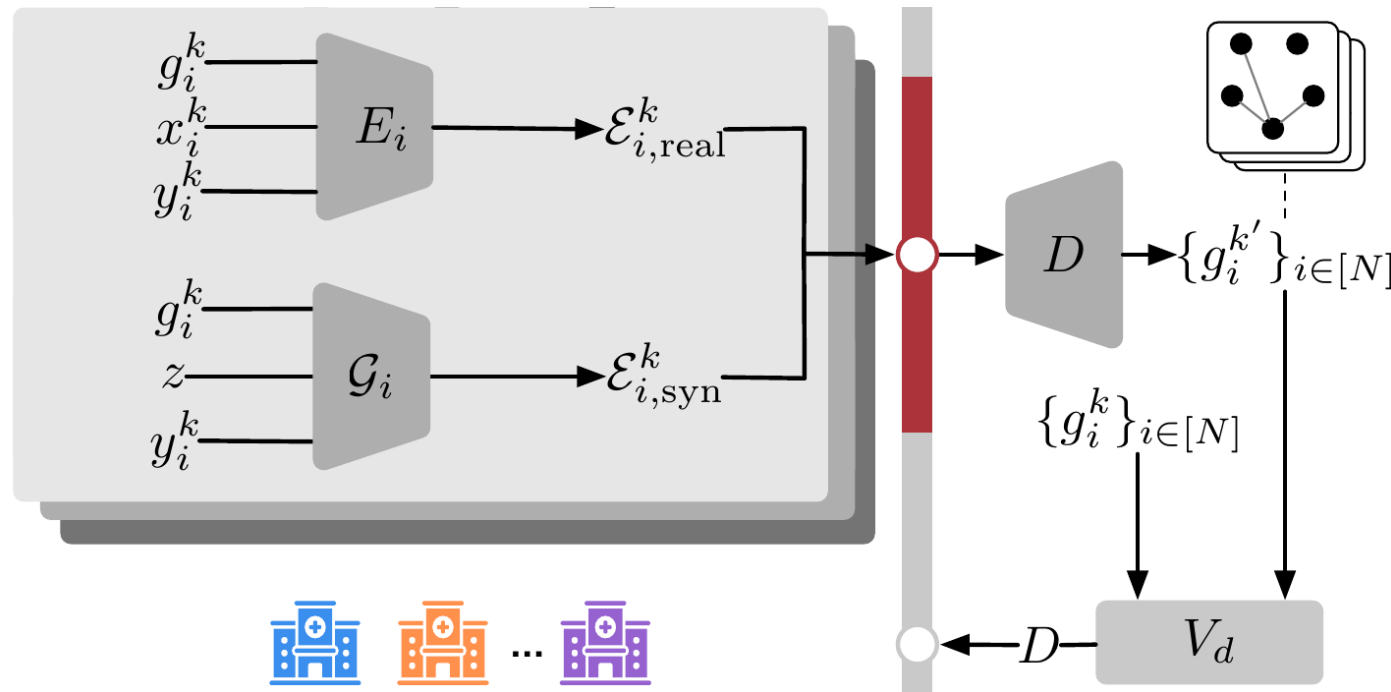
Adversarial Alignment Reduces Relational Bias

Global discriminator

Predicts the graph row from perturbed features

Local encoder and generator

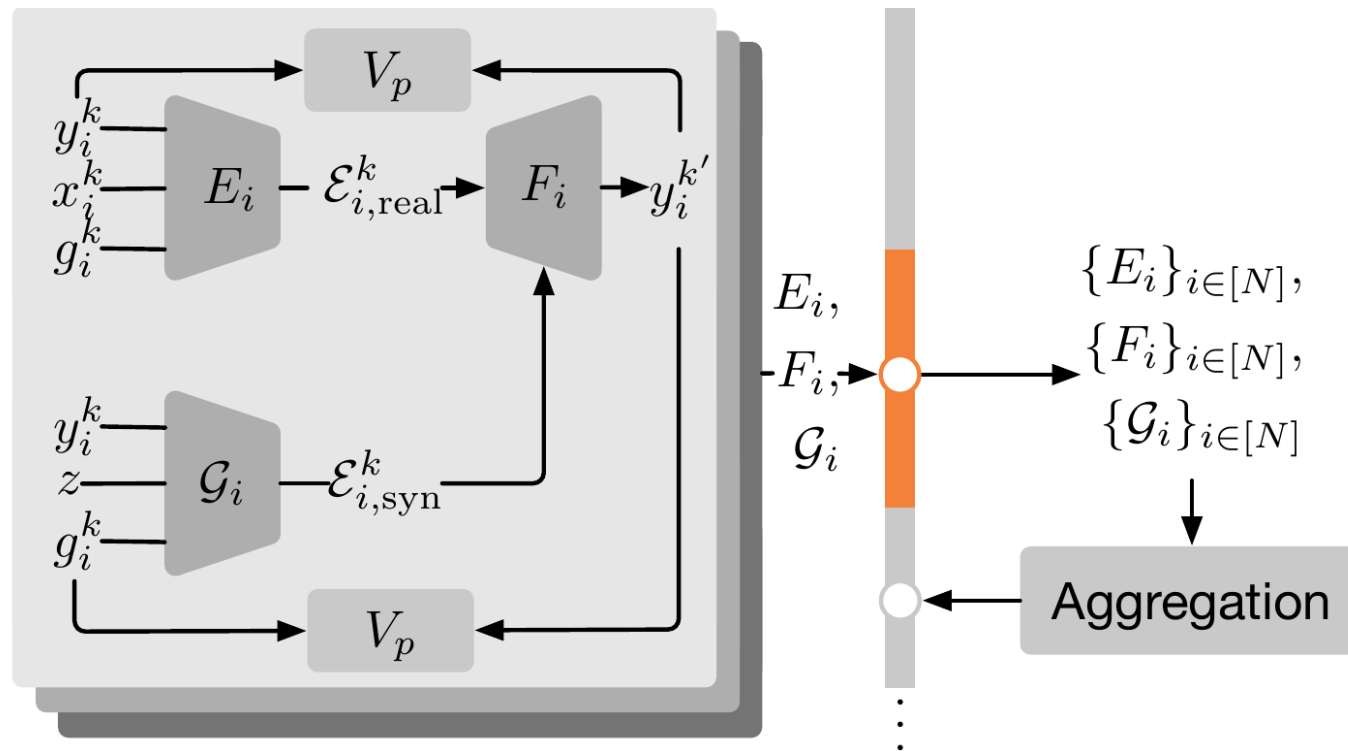
Learn features that make this reconstruction difficult



Prediction loss retains task information while the shared objective aligns representations.

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

Graph-Conditioned Replay Preserves Knowledge



Current samples

Encode x with the current graph row.

Replay

Generate latent features from noise, label and historical graph context.

Encoder inputs: scan and graph row. Replay inputs: noise, label and historical graph row.

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

TCGA-BRCA and TCIA Data

TCGA-BRCA

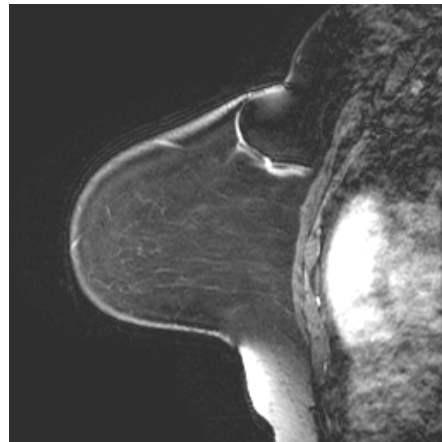
1,098 patient cases
60,660 measurements per profile
19,962 protein-coding genes

Public TCIA Collection

MR and mammography in DICOM
Linked to TCGA by patient ID



Axial T1-weighted MRI



Sagittal VIBRANT MRI

Example Imaging Record

Case: TCGA-AR-A1AQ
TCIA TCGA-BRCA archive

Linked records:
Expression · Clinical · Subtype

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," IEEE HealthCom, 2026.

[8] W. Lingle et al., "The Cancer Genome Atlas Breast Invasive Carcinoma Collection (TCGA-BRCA)," TCIA, 2016.

Experimental Setup

Federated Continual Setting

4 tasks -> 4 stages; 4 clients
Dirichlet distribution to simulate non-IID scenarios

Implementation

NVIDIA FLARE

Representative FCL Baselines

FedAvg-Adv · FedAvg Variant*
FedCIL · ICLR 2023
MFCL · NeurIPS 2023

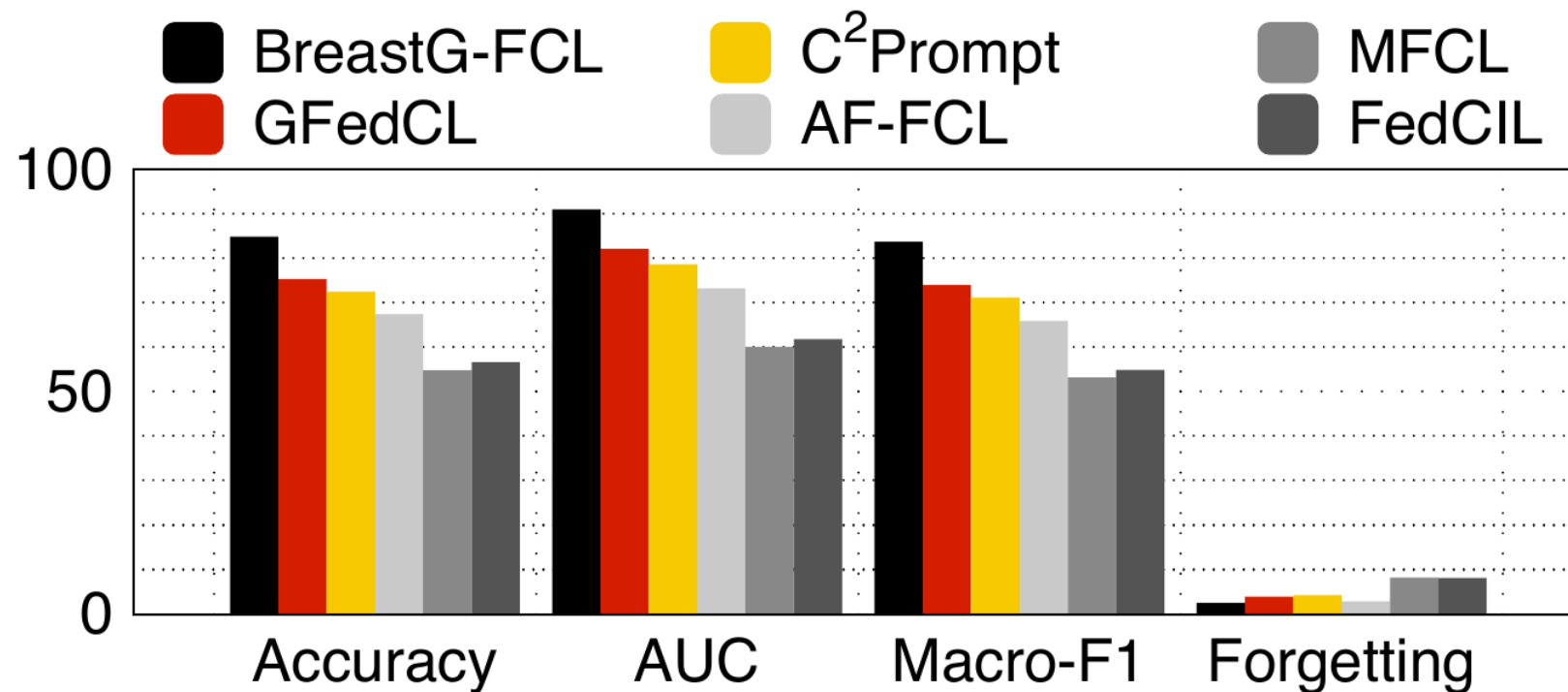
AF-FCL · ICLR 2024
C²Prompt · NeurIPS 2025
GFedCL · ICML 2026

Accuracy, AUC, Macro-F1 and forgetting

*Adversarial FedAvg baseline used in GFedCL (ICML 2026).

[5] Q. Yu et al., “BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics,” IEEE HealthCom, 2026.

BreastG-FCL Improves Predictive Performance



84.87%

Accuracy

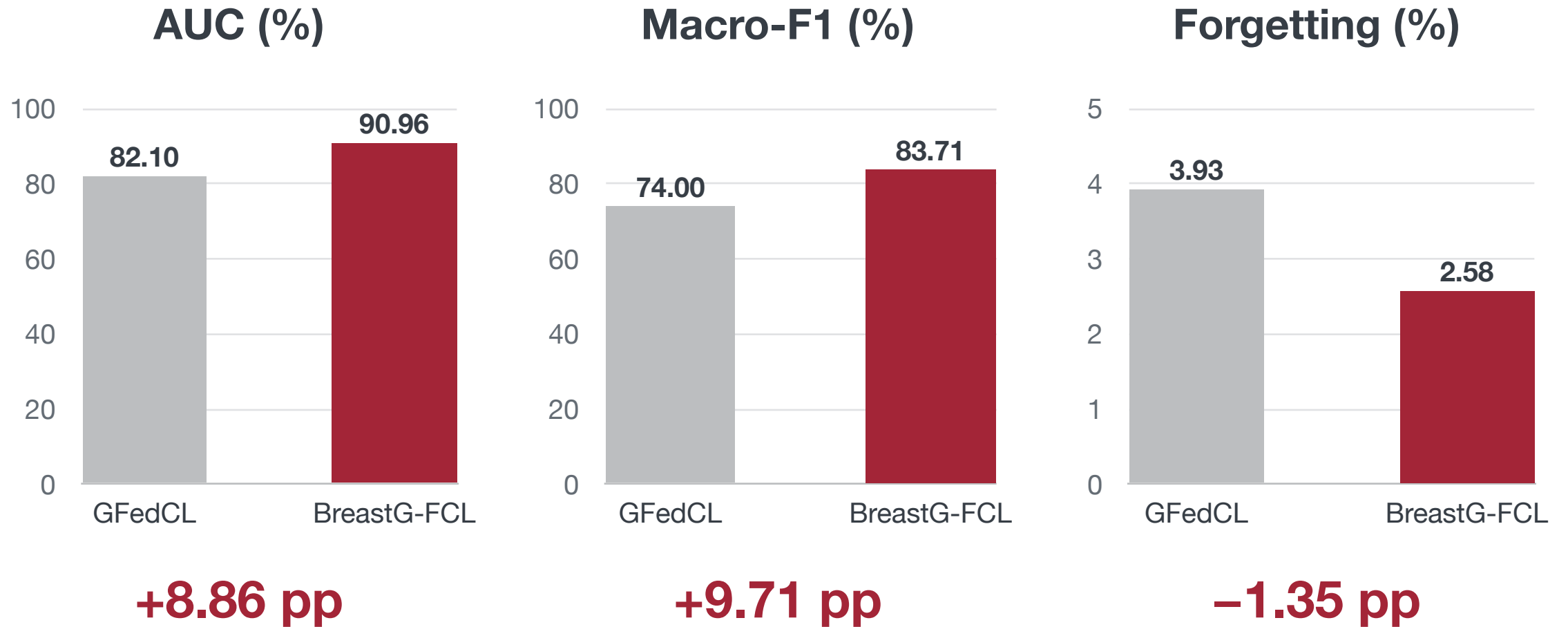
+9.55

percentage points
vs. GFedCL

Original results from Fig. 4. Classification metrics: higher is better. Forgetting: lower is better.

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

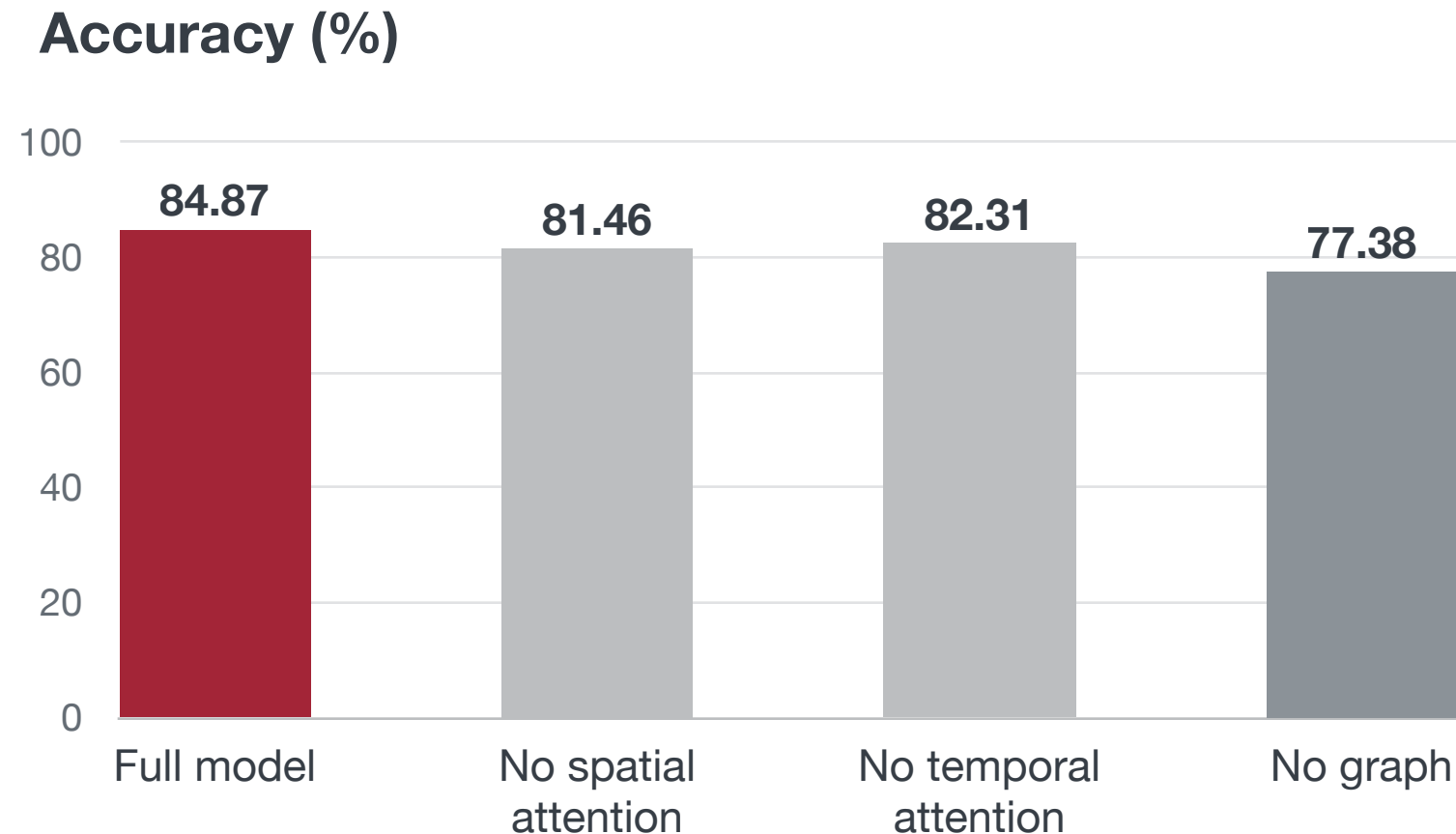
Higher Prediction Quality, Lower Forgetting



pp = percentage points. Lower forgetting means less performance loss on previous tasks.

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

Both Clinical Signals Contribute



Removing the graph

-7.49 pp

accuracy

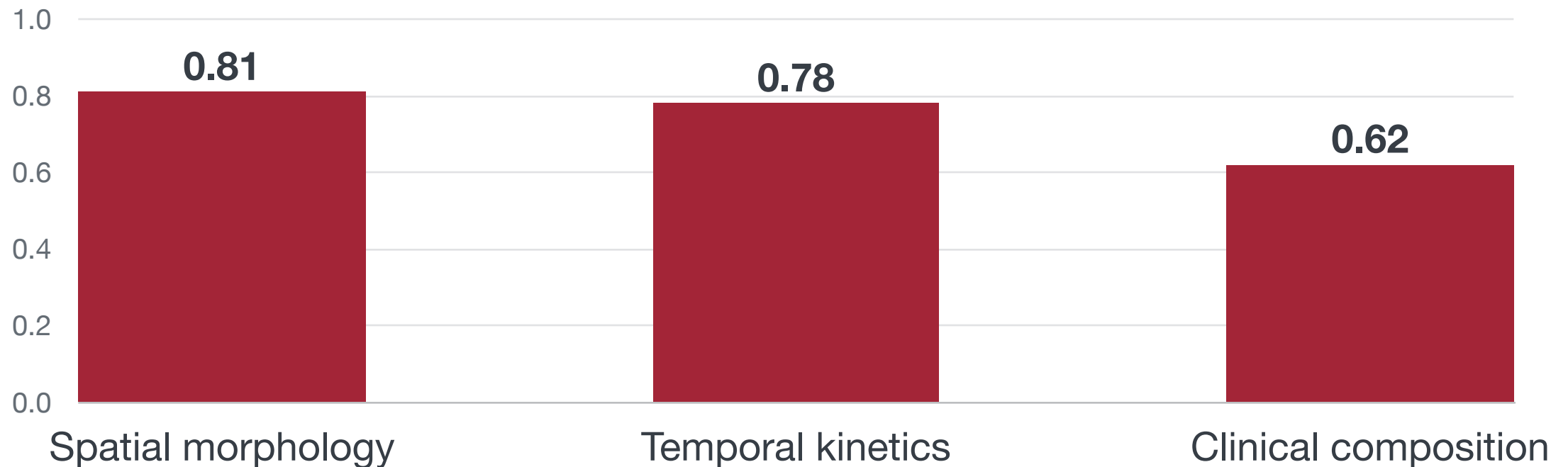
Forgetting rises from 2.58% to 4.21%.

Ablation values from the paper's text and reported deltas, Section IV-C.

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

The Learned Graph Reflects Clinical Similarity

Pearson correlation with graph edge weights



Clients with similar phenotypes receive stronger connections.

Correlation describes the learned graph; it does not establish clinical deployment validity.

[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.

BreastG-FCL

Disease-aware client relations

Tumor morphology and DCE-MRI kinetics guide replay and representation alignment.

84.87% accuracy

+9.55 percentage points over GFedCL

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[5] Q. Yu et al., "BreastG-FCL: Graph-Conditioned Federated Continual Learning for Breast Cancer Radiogenomics," *IEEE HealthCom*, 2026.





Thank You



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Q&A

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