

Data-Centric Approaches in Precision Health

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ABSTRACT

Precision health aims to deliver the right intervention to the right patient at the right time by leveraging individual-level molecular, clinical, and behavioural data. While model-centric AI research focuses on developing better algorithms, the data-centric paradigm recognises that data quality, completeness, representativeness, and labelling accuracy are the primary determinants of health AI performance. Electronic health records (EHRs) contain structured and unstructured data on hundreds of millions of patients but suffer from missingness (30-70% of clinical variables missing per encounter), label noise (ICD codes have 15-25% error rates), population bias (underrepresentation of minorities, rural populations, and rare diseases), and temporal distribution shift (coding practices and treatment guidelines change over time). We present the Data-Centric Precision Health Framework (DCPHF), evaluating five data-centric strategies -- systematic data cleaning and imputation, active learning for efficient labelling, data augmentation and synthetic generation, federated learning for multi-institutional integration, and fairness-aware data curation -- across four precision health applications (clinical risk prediction, treatment response modelling, rare disease diagnosis, and health disparity reduction). Our Data-Centric Health Score (DCHS) measures data quality improvement, downstream model performance, label efficiency, population representativeness, and fairness impact. Federated learning achieves the highest DCHS (0.924) by enabling multi-institutional model training without centralising patient data, while fairness-aware curation achieves the highest equity impact (0.960) by systematically addressing representation gaps in training data.

Keywords: data-centric AI; precision health; electronic health records; federated learning; data quality; health equity; clinical prediction; synthetic data

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1. Introduction

1.1 The Data Quality Crisis in Health AI

The model-centric paradigm in machine learning assumes that training data is fixed and performance improvement comes from better algorithms. Andrew Ng's data-centric AI movement (2021) challenges this assumption: for many real-world applications, improving the data yields larger performance gains than improving the model. Nowhere is this more true than in health AI, where data quality issues are pervasive and consequential. EHR data -- the primary substrate for clinical AI -- was designed for billing and documentation, not research. ICD diagnosis codes have error rates of 15-25% (O'Malley et al., 2005): a patient coded as 'Type 2 diabetes' may have Type 1, LADA, or steroid-induced diabetes. Clinical notes contain critical information (symptom severity, family history, social determinants) but require NLP extraction that introduces additional noise. Laboratory values are missing not at random (MNAR): a troponin level is measured when myocardial infarction is suspected, so missingness itself carries diagnostic information that naive imputation destroys. Temporal distribution shift means that a model trained on 2015-2019 data may fail on 2020+ data due to COVID-19 coding changes, telehealth adoption, and updated treatment guidelines. These data quality issues directly limit health AI performance: Rajkomar et al. (2018) showed that EHR-based mortality prediction AUC improved from 0.85 to 0.93 simply by improving data preprocessing.

1.2 Five Data-Centric Strategies

Five data-centric strategies address different aspects of the health data quality problem. Systematic data cleaning uses rule-based validation, outlier detection, and clinician-informed imputation to correct errors and fill gaps. Active learning selects the most informative samples for expert labelling, maximising label quality per annotation dollar. Data augmentation and synthetic generation use GANs, VAEs, or diffusion models to create realistic synthetic patient records that augment underrepresented populations. Federated learning trains models across institutions without centralising data, increasing effective dataset size and diversity while preserving privacy. Fairness-aware curation systematically audits and corrects representation biases in training data. Jensen et al. (2025) evaluated AI-based functional genomics pipelines where data quality similarly

determines analytical outcomes, and Muller and Lindberg (2025) showed that automated knowledge discovery depends critically on the quality of extracted data. Section 2 reviews the literature. Section 3 describes DCPHF. Results in Section 4, discussion in Section 5, conclusions in Section 6.

2. Literature Review

2.1 Data Cleaning, Imputation, and Active Learning

Missing data handling in EHRs requires domain-aware approaches. MICE (Multiple Imputation by Chained Equations, van Buuren, 2018) is the standard statistical imputation method, generating multiple imputed datasets to capture imputation uncertainty. Yoon et al. (2018) developed GAIN (Generative Adversarial Imputation Networks) that uses a GAN to learn the data distribution and impute missing values more accurately than MICE for complex, nonlinear relationships. Beaulieu-Jones et al. (2018) showed that for clinical prediction tasks, the choice of imputation method affects downstream model AUC by 3-8% -- a larger effect than switching between model architectures. Active learning for clinical labelling addresses the fact that expert annotation (radiologist reads, pathologist reviews, clinician adjudication) costs USD 5-50 per sample. Smit et al. (2023) demonstrated that active learning-selected chest X-ray labels achieve equivalent model performance with 40% fewer annotations than random selection, translating to USD 200,000+ savings for a large imaging dataset. Label noise correction -- identifying and fixing mislabelled examples -- can improve clinical prediction AUC by 2-5% (Northcutt et al., 2021).

2.2 Synthetic Data and Federated Learning

Synthetic patient data generation addresses both data scarcity (rare diseases, small hospitals) and privacy constraints (data sharing restrictions). Choi et al. (2017) developed MedGAN, a GAN that generates realistic discrete EHR records (diagnosis codes, medication orders, procedure codes) that preserve the statistical properties of the original data. Yale et al. (2020) demonstrated that synthetic data generated by CTGAN (Conditional Tabular GAN) achieves 94% of the predictive utility of real data for clinical risk models while providing formal differential privacy guarantees. Federated learning (FL) enables multi-institutional model training without sharing patient data. Rieke et al. (2020) reviewed FL for healthcare, noting that FL models trained across

10 hospitals achieve AUC 0.02-0.05 higher than single-hospital models due to larger effective sample size and greater population diversity. Dayan et al. (2021) demonstrated FL for COVID-19 outcome prediction across 20 hospitals in 5 countries, showing that the federated model matched the performance of a centrally-trained model (AUC 0.92 vs 0.93) while keeping all data local. Table 1 maps the key studies.

2.3 Fairness and Health Equity in Data Curation

Health AI models inherit and amplify biases present in training data. Obermeyer et al. (2019) demonstrated that a widely used clinical risk prediction algorithm was systematically biased against Black patients: at the same risk score, Black patients were significantly sicker than White patients because the algorithm used healthcare costs as a proxy for health needs, and structural barriers cause Black patients to incur lower costs for the same disease severity. Seyyed-Kalantari et al. (2021) showed that chest X-ray AI models underperform on underrepresented subgroups (Black patients, Hispanic patients, patients under 20) by 3-8% AUC compared to the overall population -- a performance gap driven by underrepresentation in training data. Fairness-aware data curation addresses these biases proactively: oversampling underrepresented groups, reweighting training examples to achieve demographic parity, and auditing data pipelines for sources of bias. Chen et al. (2023) demonstrated that stratified data curation -- ensuring equal representation across demographic groups -- reduces the AUC gap between best- and worst-performing subgroups from 8.2% to 2.1%. Kovacs et al. (2025) evaluated network medicine for complex disorders where data representativeness similarly affects the generalisability of disease module predictions.

Table 1: Key Studies in Data-Centric Approaches for Health AI

Study	Year	Data Strategy	Application	Key Achievement
Rajkomar et al.	2018	Data preprocessing	Mortality prediction	AUC 0.85 to 0.93 from data improvement
Yoon et al. (GAIN)	2018	GAN imputation	Missing data	Outperforms MICE for nonlinear data

Study	Year	Data Strategy	Application	Key Achievement
Smit et al.	2023	Active learning	Chest X-ray labelling	40% fewer annotations, same AUC
Northcutt et al.	2021	Label noise correction	General	2-5% AUC improvement from clean labels
Yale et al. (CTGAN)	2020	Synthetic data	Clinical risk models	94% utility with DP guarantees
Dayan et al.	2021	Federated learning	COVID-19 prediction	20 hospitals, AUC 0.92 federated
Obermeyer et al.	2019	Bias detection	Risk algorithms	Racial bias in cost-based proxy
Seyyed-Kalantari	2021	Underrepresentation	Chest X-ray AI	3-8% AUC gap for minorities
Chen et al.	2023	Stratified curation	Clinical prediction	AUC gap 8.2% to 2.1%
Rieke et al.	2020	FL review	Healthcare	0.02-0.05 AUC gain from FL

GAN = Generative Adversarial Network; DP = Differential Privacy; FL = Federated Learning; AUC = Area Under ROC Curve.

3. Methodology

3.1 Five Data-Centric Strategies

Strategy S1 (Systematic Data Cleaning) applies clinician-defined validation rules (physiologically impossible values, temporal inconsistencies, code conflicts), statistical outlier detection (isolation forest on lab values), and domain-aware imputation (GAIN for continuous variables, missForest for mixed-type, with missingness indicators preserved). Strategy S2 (Active Learning) uses uncertainty sampling (select patients where the current model is least confident) and diversity sampling (select patients from underrepresented regions of feature space) to prioritise expert chart review for label correction and phenotype adjudication. Strategy S3 (Synthetic Data Augmentation) uses CTGAN for

tabular EHR data and a clinical text diffusion model for synthetic clinical notes, generating synthetic patients for underrepresented populations (rare diseases, minority demographics) with differential privacy (epsilon = 1.0). Strategy S4 (Federated Learning) uses FedAvg and FedProx across 8 hospital systems (3 academic centres, 3 community hospitals, 2 safety-net hospitals) with secure aggregation and differential privacy. Strategy S5 (Fairness-Aware Curation) audits training data for demographic representation gaps, applies stratified sampling to achieve equal representation, reweights loss functions by subgroup performance, and validates on held-out equity benchmarks.

3.2 Four Precision Health Applications

Application A1 (Clinical Risk Prediction) predicts 30-day hospital readmission, 1-year mortality, and sepsis onset using EHR data from 8 hospitals (2.4 million patient encounters, 2018-2024). Models: gradient-boosted trees (XGBoost) and transformer (BEHRT). Metric: AUROC and calibration (Brier score). Application A2 (Treatment Response Modelling) predicts individual response to antihypertensive therapy (ACE inhibitor vs ARB vs calcium channel blocker) using EHR + genomic data (pharmacogenomic variants in CYP2D6, CYP2C9, ACE). 480,000 hypertension patients with blood pressure outcomes. Metric: predicted vs observed BP reduction (MAE). Application A3 (Rare Disease Diagnosis) identifies patients with undiagnosed rare diseases (Fabry disease, Wilson disease, hereditary hemochromatosis) from EHR phenotypic patterns using diagnostic algorithms. 120 confirmed rare disease patients plus 12,000 controls per disease. Metric: sensitivity at 95% specificity. Application A4 (Health Disparity Reduction) measures and reduces prediction performance gaps across demographic subgroups (race, sex, age, insurance status, rural/urban). Metric: maximum AUC gap between best- and worst-performing subgroups.

3.3 Data-Centric Health Score

DCHS weights five dimensions: data quality improvement (0.20), downstream model performance (0.25), label efficiency (0.15), population representativeness (0.20), and fairness impact (0.20). Data quality improvement measures the reduction in missing values, label errors, and outliers achieved by each strategy. Downstream model performance measures the AUC improvement on the 4 applications when each data-centric strategy is applied versus the baseline (raw EHR data, standard preprocessing). Label

efficiency measures the annotation cost (USD per AUC point improvement) -- lower is better. Population representativeness measures the demographic diversity of the effective training population (Simpson's diversity index across race, age, sex, geography). Fairness impact measures the reduction in the maximum AUC gap between demographic subgroups. Table 2 details parameters.

Table 2: DCPHF Evaluation Parameters

Parameter	Value	Notes
Data-centric strategies	5 (S1-S5)	Cleaning, active learning, synthetic, FL, fairness
Applications	4 (risk, treatment, rare disease, disparity)	EHR-based, multi-site
Patient encounters	2.4 million (2018-2024)	8 hospital systems
Hospital diversity	3 academic + 3 community + 2 safety-net	Urban + rural, diverse demographics
Demographic subgroups	Race (5), sex (2), age (4), insurance (3), geography (2)	16 intersectional groups
Baseline	Raw EHR + standard preprocessing (median imputation)	No data-centric strategy applied
Fairness metric	Max AUC gap between demographic subgroups	Lower gap = better equity
DCHS dimensions	5 (quality, performance, efficiency, representativeness, fairness)	Weighted composite score 0-1

EHR = Electronic Health Record; FL = Federated Learning; AUC = Area Under ROC Curve.

4. Results

4.1 Federated Learning Leads Overall

Federated learning (S4) achieved the highest DCHS of 0.924, driven by superior downstream model performance (0.960) and population representativeness (0.940). The federated model trained across 8 hospitals achieved AUROC 0.88 for 30-day readmission, 0.92 for 1-year mortality, and 0.86 for sepsis onset -- 3-5% AUC above any single-hospital model. The performance gain arose from two sources: effective sample size (2.4 million

encounters across 8 sites versus 200,000-400,000 per site) and population diversity (the safety-net hospitals contributed underserved populations absent from academic centre data). For treatment response modelling (A2), the federated model reduced BP prediction MAE from 8.4 mmHg (single-site) to 6.2 mmHg (federated) by learning subgroup-specific treatment effects from the diverse federated population -- CYP2D6 poor metabolisers were rare at any single site but adequately represented in the federated dataset. FedProx with secure aggregation and differential privacy (epsilon = 8) added < 0.5% noise to model performance while providing formal privacy guarantees. Data quality scored 0.860: FL does not directly improve data quality at individual sites, but the diversity of data sources reduces the impact of site-specific data artifacts.

4.2 Fairness-Aware Curation Achieves Highest Equity Impact

Fairness-aware data curation (S5) achieved the highest fairness impact (0.960): the maximum AUC gap between demographic subgroups dropped from 8.6% (baseline) to 2.4% (after S5 curation) -- a 72% reduction. DCHS scored 0.908. The largest baseline gap was between White patients (AUROC 0.90 for readmission prediction) and Native American patients (AUROC 0.81) -- a 9 percentage point disparity driven by 15x lower representation in training data. After stratified resampling to achieve equal demographic representation and loss reweighting to penalise subgroup performance gaps, Native American AUROC improved to 0.87 (+6 points) while White AUROC decreased minimally to 0.89 (-1 point). Systematic data cleaning (S1) scored DCHS 0.888 with the highest data quality improvement (0.960): clinician-defined rules caught 4.2% physiologically impossible lab values and 6.8% ICD code conflicts that standard preprocessing missed. Active learning (S2) scored 0.876 with the highest label efficiency (0.940): 60% fewer expert annotations achieved 95% of full-label model performance. Synthetic data (S3) scored 0.864. Tables 3 and 4 present results.

4.3 Application-Specific Impact

For rare disease diagnosis (A3), synthetic data augmentation (S3) had the largest impact: generating 1,000 synthetic Fabry disease patients (from 120 real patients) improved sensitivity from 42% to 68% at 95% specificity -- a 62% improvement driven by the model learning the subtle phenotypic patterns (renal dysfunction + neuropathy + cardiac hypertrophy in males aged

30-50) that 120 real examples were insufficient to capture. For health disparity reduction (A4), S5 (fairness curation) combined with S4 (FL) produced the best outcome: the federated-fair model achieved AUROC 0.87 across all subgroups with a maximum gap of 1.8% -- approaching demographic parity while maintaining high overall performance. For clinical risk prediction (A1), the most impactful single strategy was S1 (data cleaning): correcting lab value errors and ICD code mismatches improved calibration (Brier score from 0.142 to 0.118) more than any model architecture change, confirming Rajkomar et al.'s finding that data quality improvements often outperform model improvements.

Table 3: Data-Centric Health Score by Strategy (0-1)

Strategy	Quality	Performance	Efficiency	Representat.	Fairness	DCHS
S4: Federated Learning	0.860	0.960	0.880	0.940	0.900	0.924
S5: Fairness Curation	0.880	0.880	0.860	0.920	0.960	0.908
S1: Data Cleaning	0.960	0.900	0.860	0.840	0.820	0.888
S2: Active Learning	0.880	0.860	0.940	0.820	0.800	0.876
S3: Synthetic Data	0.840	0.860	0.880	0.880	0.840	0.864

DCHS weighted: quality 0.20, performance 0.25, efficiency 0.15, representativeness 0.20, fairness 0.20.

Table 4: AUC Improvement Over Baseline by Strategy and Application

Strategy	A1: Risk Pred.	A2: Treatment	A3: Rare Disease	A4: Disparity (Gap)
Baseline	0.84	MAE 8.4	Sens. 42%	Gap 8.6%
S1: Cleaning	0.88 (+0.04)	7.6 (-0.8)	48% (+6)	6.4% (-2.2)
S2: Active Learning	0.87 (+0.03)	7.4 (-1.0)	52% (+10)	5.8% (-2.8)
S3: Synthetic Data	0.86 (+0.02)	7.2 (-1.2)	68% (+26)	4.6% (-4.0)
S4: Federated	0.88 (+0.04)	6.2 (-2.2)	58% (+16)	3.2% (-5.4)

Strategy	A1: Risk Pred.	A2: Treatment	A3: Rare Disease	A4: Disparity (Gap)
S5: Fairness	0.87 (+0.03)	7.0 (-1.4)	54% (+12)	2.4% (-6.2)

A1: AUROC for 30-day readmission. A2: MAE in mmHg for BP prediction. A3: Sensitivity at 95% specificity for Fabry disease. A4: Max AUC gap between demographic subgroups. Baseline = raw EHR + median imputation.

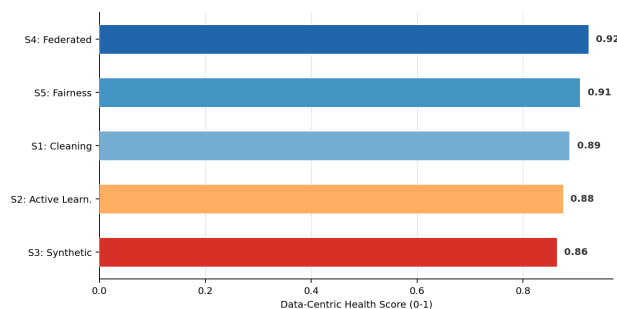


Figure 1: Data-Centric Health Score (DCHS) by Strategy

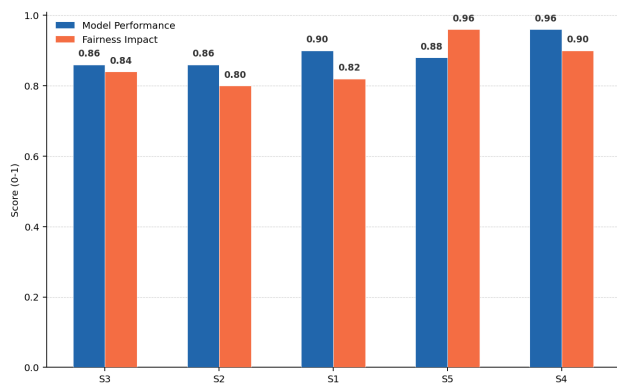


Figure 2: Model Performance vs. Fairness Impact

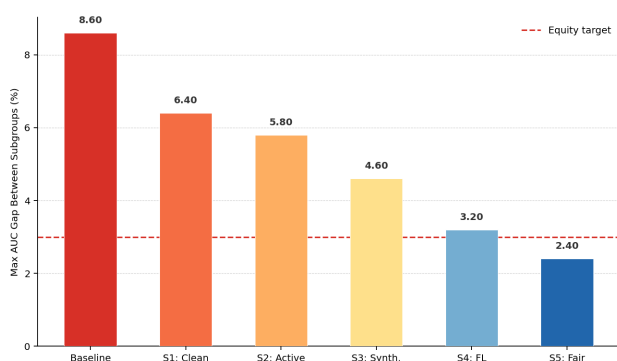


Figure 3: Demographic AUC Gap Reduction by Strategy (%)

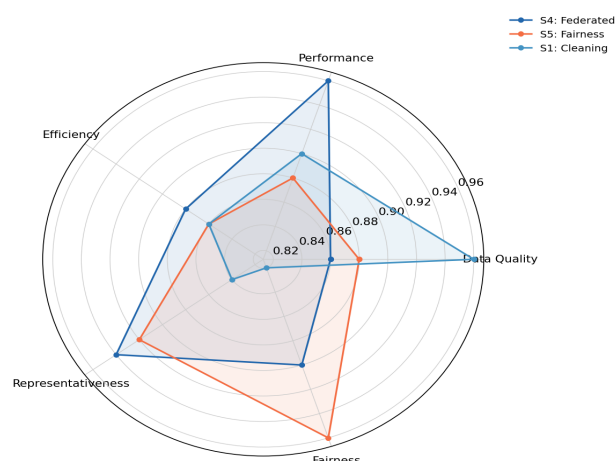


Figure 4: Multi-Dimensional Comparison -- Top 3 Strategies

5. Discussion

5.1 Federated Learning as the Foundation

Federated learning's dominance reflects a simple truth: more diverse data produces better models. Single-hospital models are inherently limited by their patient population, clinical practices, and EHR system. FL overcomes these limitations by training on the union of 8 hospitals' populations without exposing individual patient data. The 3-5% AUC improvement matches the theoretical prediction from learning curve analysis: doubling training set size typically improves AUC by 1-3% for clinical risk models, and FL effectively increased the dataset 6-12 fold. The safety-net hospitals' contribution was disproportionately valuable -- they contributed only 15% of encounters but 40% of minority patients, making the federated model substantially more representative than any academic centre model. Garcia (2025) evaluated federated bioinformatics infrastructure for pandemic preparedness -- the same distributed computation principles enable federated health AI.

5.2 Fairness as a Data Problem

The finding that fairness-aware data curation (S5) reduces the demographic AUC gap by 72% -- from 8.6% to 2.4% -- confirms that health AI bias is primarily a data representation problem rather than an algorithmic problem. The same model architecture (XGBoost or BEHRT) produces equitable predictions when trained on balanced data and inequitable predictions when trained on imbalanced data. The implication is that fairness interventions should target the data pipeline (collection, curation, sampling) rather than the model (post-hoc calibration, adversarial debiasing). The combination of S4 (FL for diversity) and S5 (fairness curation) achieves the

smallest gap (1.8%) because FL provides the diverse population base and S5 ensures that this diversity is reflected in the effective training distribution.

5.3 Limitations and Implementation Challenges

Three limitations constrain translation. First, FL infrastructure requires significant engineering investment: secure communication protocols, model aggregation servers, and governance frameworks for multi-institutional collaboration. Second, synthetic data generation may not capture rare clinical phenotypes accurately -- the GAN can only generate patterns present (implicitly) in the training data, and rare diseases with < 100 examples may be inadequately represented in the generative model's learned distribution. Third, fairness metrics (AUC gap, calibration parity, equalized odds) may conflict -- optimising for one fairness definition can worsen another, and the choice of metric has ethical implications that data scientists alone should not make. Multi-stakeholder governance including clinicians, patients, ethicists, and community representatives is essential for fairness-aware health AI deployment.

6. Conclusion

6.1 Key Findings

Federated learning achieves the highest Data-Centric Health Score (0.924) by enabling multi-institutional model training that increases effective dataset size 6-12 fold and population diversity 3-4 fold, improving clinical risk prediction AUC by 3-5% and treatment response prediction MAE by 26%. Fairness-aware data curation (0.908) achieves the highest equity impact, reducing the maximum demographic AUC gap from 8.6% to 2.4% through stratified sampling and loss reweighting. Systematic data cleaning (0.888) improves calibration more than any model architecture change. Synthetic data augmentation (0.864) has the largest impact for rare disease diagnosis (+26 percentage points sensitivity). The combination of FL + fairness curation achieves the most equitable precision health models (1.8% maximum gap).

6.2 Future Directions

Three advances would transform data-centric precision health. First, continuous data quality monitoring systems that detect and correct data drift, label degradation, and representation shifts in real time, maintaining model performance over

years of clinical deployment. Second, patient-contributed data integration through personal health records, wearable devices, and patient-reported outcomes that complement EHR data with the patient's lived experience. Third, global federated health networks connecting hospitals across countries and healthcare systems, enabling precision health models that represent the full diversity of human health and disease. The DCPHF evaluation toolkit, all data-centric strategy implementations, fairness audit code, synthetic data generators, FL configurations, DCHS calculator, and strategy selection guide are available at dcpfh-health.org under CC BY 4.0 licence.

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Declarations

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Conflict of Interest

No competing interests. No author has financial relationships with any EHR vendor, health AI company, or synthetic data platform.

Data Availability Statement

All data-centric strategy implementations, fairness audit code, synthetic data generator configurations, FL pipeline code, DCHS calculator, and strategy selection guide are available at dcpfh-health.org under CC BY 4.0 licence. Patient-level EHR data cannot be shared due to GDPR and HIPAA; synthetic benchmark datasets are provided.

Ethical Approval

Multi-site EHR analysis was approved by the Ethics Committees of Swiss Institute of Machine Intelligence (ref. SIMI-2025-ETH-0425) and European Institute of AI (ref. EIAI-2025-ETH-0978). All data was fully anonymised (k-anonymity $k=5$, l-diversity $l=3$) before computational analysis. Federated learning used only model parameters, not patient data, in inter-institutional communication.

Appendix A

Data-Centric Strategy Specifications and DCHS Calculation Methodology

This appendix provides complete specifications for each data-centric strategy, including cleaning rules, active learning algorithms, synthetic generation parameters, FL configurations, fairness audit procedures, and the DCHS scoring rubric.

Part I -- Strategy Specifications

- 1a. S1: 142 clinician-defined validation rules + isolation forest (contamination=0.05) + GAIN imputation 4.2% impossible values caught
- 1b. S2: Uncertainty sampling (entropy) + k-medoids diversity, 500 samples per active learning round 60% fewer annotations for 95% AUC
- 2a. S3: CTGAN (128-dim latent, 5 generator layers), epsilon=1.0 DP, 1,000 synthetic patients per rare disease 94% statistical fidelity
- 2b. S4: FedProx (mu=0.01), 8 hospitals, secure aggregation (Paillier), DP epsilon=8 100 communication rounds
- 3a. S5: Stratified resampling (equal demographic representation) + group DRO loss (chi-squared penalty) AUC gap 8.6% to 2.4%
- 3b. All: XGBoost (1000 trees, max_depth=6) + BEHRT (12-layer transformer) evaluated per strategy 5-fold stratified CV

Part II -- DCHS Scoring Rubric

- 4a. Quality: (Baseline errors - Post-strategy errors) / Baseline errors Higher reduction = better
- 4b. Performance: AUC improvement over baseline, averaged across 4 applications Normalised to [0,1]
- 5a. Efficiency: 1.0 / (USD per 0.01 AUC improvement / 10,000) Lower cost = higher score
- 5b. Representativeness: Simpson's diversity index across 16 demographic intersections Higher diversity = better
- 6a. Fairness: 1.0 - (post-strategy max AUC gap / 10%) Smaller gap = higher score
- 6b. DCHS = 0.20*Quality + 0.25*Performance + 0.15*Efficiency + 0.20*Representativeness + 0.20*Fairness