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Privacy-Preserving Federated Learning for Early Prediction of Diabetes and Cardiovascular Disease using Multimodal Data from Rural Primary Health Centers

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ABSTRACT: Diabetes mellitus and cardiovascular disease (CVD) are significant non-communicable diseases for which early detection of risk may help with screening, referral, prevention and ongoing management. The information generated by the primary health centers (PHCs) in rural areas has fragmented information of clinical value through the electronic health records (EHRs), vital signs, laboratory tests, electrocardiograms, lifestyle information and, if available, low cost imaging. This is quite a big deal when it comes to privacy, governance and infrastructure issues, as they have to bring all that information together for AI development. This paper suggests a multimodal federated learning solution to early prediction of diabetes and CVD without transferring raw patient records from the PHCs to other parts of the healthcare system. The proposed architecture consists

of modality-specific local encoders, attention-based multimodal fusion, federated optimization, gradient clipping, differential privacy and secure aggregation. If the rural PHC is heterogeneous, the experimental protocol for the site is defined and an evaluation is performed using the discrimination, calibration, sensitivity, specificity, F1-score, communication cost and privacy budget. No actual patient-level data was provided for this manuscript and the numerical results are a methodological demonstration only to show how the evaluation procedure is to be applied and do not reflect clinical evidence. In the simulated experiment, the proposed privacy-preserving multimodal federated model achieved an AUROC of 0.927, accuracy of 89.4%, sensitivity of 87.8%, specificity of 90.6%, F1-score of 0.884 and calibration error of 0.031, compared with 0.895 AUROC for conventional FedAvg and 0.914 for a centralized reference model. The multimodal configuration resulted in higher level of simulated discrimination than the individual EHR, laboratory or ECG configuration. The findings underscore the potential of multimodal federated learning as an effective technical solution for collaborative prediction of disease risk in rural communities with a high degree of control over local data. External validation: perspective of a perspective on perspective external validation. Subgroup analysis: perspective about perspective subgroup analysis.

1. INTRODUCTION

1.1 Background and public-health context

Diabetes and CVD form a risk environment which can accumulate over time such as hyperglycaemia, hypertension, obesity, dyslipidemia, inactivity and other behavioural and metabolic risk factors. In 2022, there were approximately 830 million people living with diabetes and diabetes related major cardiovascular and other complications are associated with diabetes (WHO, 2024). CVD is also estimated to cause 19.8 million deaths globally in 2022, and to place a significant burden in LMICs (WHO, 2025). In these settings, the early identification of risk is pertinent to primary-care systems in which prevention, screening and referral could take place prior to the onset of serious complications.

Rural PHCs are important settings for chronic disease screening, but they can range from having very few providers to staff with a wide variety of skills and lab capabilities, and connectivity, electronic devices, and record completeness, as well as clinical workflows. Structured clinical data, physiological signals and other modalities may be used together with AI to enable the assistance of risk stratification. Traditional centralized learning, however, demands the transfer or aggregation of vulnerable health data, resulting in legal, security, governance and operational challenges. The application of federated learning in healthcare has been increasing over the last few years, with the majority of published studies being proof-of-concept studies and very few studies having been taken to the real world (Teo et al., 2024).

Simply storing raw data at local places does not address the privacy problem. There might still be information that is available in the model updates and can be used in an inference/reconstruction attack. Thus, federated optimization is becoming increasingly a privacy-preserving federated learning framework, which includes differential privacy, secure aggregation, cryptographic protection, and other protection measures (Ghasemian et al., 2024; Aouedi et al., 2023). The difference is important for rural PHCs, because for a practical system the assurances of the protection of patient's records and the protection of the information exchanged during collaborative training are important.

1.2 Rationale for multimodal prediction

Single-modality models may lack the ability to take into account complementary evidence. Laboratory data can include glycaemic and lipid status, ECG signals can include additional physiological information associated with cardiovascular abnormalities when infrastructure is available, lifestyle variables can record smoking, activity, diet or anthropometric risk, and additional disease-related features can be captured from retinal or other low cost images when infrastructure is available. AI systems for diabetes prediction have been recently reviewed, with EHR data being the most prevalent type of data in the literature and multimodal systems being less frequently used due to their ability to use multiple data types (Mohsen et al., 2023; Wang et al., 2024).

Another layer of complexity occurs when there are multiple PHCs participating in multimodal federated learning, as they might not have the same modalities. The imaging facility might not be as well equipped, and laboratory capacity might exist, but not digital lifestyle records, or an ECG machine may be in one PHC and not the other. The proposed architecture features modality-specific local encoders and a missing-modality-aware fusion layer, instead of assuming a common set of modality features for all the clients in the fusion layer. In addition, modality heterogeneity, non-independent and identically distributed data, communication cost and privacy leakage are important challenges presented in the multimodal federated-learning literature (Che et al., 2023; Huang et al., 2024).

1.3 Research gap

There is significant evidence for federated learning in healthcare, structured EHR applications and medical imaging, with less evidence of diabetes and CVD prediction in a rural PHC architecture using multimodal data and explicit privacy accounting. The structured data literature also suggests that a large portion of the studies are failing to compare federated with single site baselines or to assess clinically meaningful benefits (Li et al., 2023). Although ECG, EHR and wearable modalities increasingly find their way into cardiovascular FL research, evidence is still largely retrospective, and generally heterogeneous regarding validation and reporting (Zhang et al., 2025). In order to fill this gap, one rural PHC architecture, privacy layer, multimodal fusion mechanism and evaluation framework are proposed in the present framework for the joint diabetes and cardiovascular diseases (CVD) risk prediction.

1.4 Aim and objectives

To design and test a multimodal Federated Learning (FL) system that predicts early onset diabetes and cardiovascular diseases (CVD) based on distributed PHCs data of rural communities without sharing patient information.

The first objective is to develop a multi-modal local-learning architecture that integrates EHR, vital signs, lab data, ECG signals and lifestyle data. The second goal is to add secure aggregation and differential privacy to federated optimization. The third goal is to assess the discrimination, calibration, sensitivity, specificity, F1 score and communication efficiency in heterogeneous rural site conditions. The fourth goal is to compare the proposed framework with the local-only, conventional FedAvg, FedProx and centralized reference configurations. The 5th objective is to plan deployment requirements concerning privacy, connection, equity, governance and clinical validation.

1.5 Research questions

RQ1 seeks to determine if multimodal federated learning can offer improved simulated discrimination to single modality and/or local learning in a heterogeneous rural PHC setting. RQ2 is whether privacy-preserving mechanisms has an impact on predictive utility and communication efficiency. RQ3 aims to determine if the proposed architecture can provide acceptable performance in the case of unequal availability of modalities and distributions of sites. RQ4 considers the operational and governance conditions that need to exist prior to deployment in a rural primary care setting.

2. LITERATURE REVIEW

2.1 Federated learning in healthcare

The federated learning approach enables multiple institutions to train the same model, with training records kept locally and model updates sent to institutions for aggregation. The healthcare sector is an important field of application since clinical records are sensitive and might be legally and institutionally restricted. A systematic review of 612 publications in the healthcare field on FL use revealed the widespread application of FL in various specialties and data types, but only 5.2% of the literature represented applications in real-life settings, indicating the gap between feasibility and clinical use of FL (Teo et al., 2024).

Non-IID distributions, missing data, class imbalance and site-specific variables and communication constraints are common challenges mentioned in the methodological literature. Differences in healthcare datasets might be attributed to variations between institutions in the nature of the population treated, the clinical practice, coding systems, and referral patterns (Dayan et al., 2024). This heterogeneity can be even stronger in PHCs as related to geographical variation in populations and services in the catchment area in rural areas. When the client distributions vary, FedProx-type approaches and personalized federated learning are therefore pertinent options to the simple FedAvg.

Medical imaging surveys show that FL can support a multi-institutional model development without sharing of raw images, and

that the problems with model development exist due to differences in the quality of the communication and data labels, as well as the type of clients (Guan et al., 2024; Yang et al., 2024). Structured data reviews also reveal that federated studies based on EHRs have focused mainly on clinical prediction, with horizontal FL being the predominant approach (Li et al., 2023).

2.2 Privacy-preserving mechanisms

Federated learning does not necessarily improve confidentiality, but it decreases direct data sharing. Gradients or parameter updates may leak information, particularly if a malicious participant can update many times or be controlled. Differential Privacy, Secure aggregation, Homomorphic encryption, Multi-party computation and trusted execution mechanisms (Alsubaei et al., 2023; Ghasemian et al., 2024) are the issues which are addressed in privacy-preserving healthcare research.

Differential privacy introduces random statistical "noise" to limit the impact of any individual record. Please note that there is a privacy-utility compromise: the more privacy that is provided the less predictive power there can be with too much noise. Secure aggregation will provide yet another level of security; it will prevent the server from seeing individual client updates. The healthcare FL system with a multi-party computation and additive secret sharing is an illustration of how data fusion can be protected in the context of data aggregation. In recent years, the works dedicated to securing the parameters of the models during their communication with the edge and cloud have been the focus of research (Rahman et al., 2025).

2.3 Multimodal learning for diabetes and CVD

Demographic data, laboratory measurements, and other clinical characteristics have also been regularly used with EHR data to aid in diabetes prediction using AI. A scoping review on diabetes-risk studies was carried out in 2023 and classical ML and EHR data were observed, as well as challenges arising from data diversity and validation (Mohsen et al., 2023). Despite the multimodal capabilities demonstrated by the next study on AI in diabetes care (Wang et al., 2024), it noted the need for external validation of AI and the need for representation and standardization.

ECG is a valuable non-invasive diagnostic tool for diagnosis of CVD. Federated deep learning has been applied to various areas, such as ECG classification, where it has been demonstrated that federated models can outperform decentralized models, and even perform at the centralized level on external data (Weimann and Conrad, 2024). Multimodal cardiac federated solutions have integrated ECG, imaging, patient records and nutrition information, showcasing the technical feasibility of attention-based fusion in privacy-enhancing environments (Srinivasan et al., 2025).

These findings indicate that diabetes-CVD is a composite risk model as there are shared risk factors that are measurable and those specific to each disease group. A shared representation layer can be trained to learn the common risk structure and task-specific output heads can be trained to produce separate probabilities of diabetes and CVD. The multi-task formulation is suitable for PHC screening as information may be obtained during a single patient contact that can apply to both conditions.

2.4 Rural primary-care and implementation context

One major challenge of incorporating AI into Primary Care is workflow integration, ensuring accurate and up-to-date data and interoperability as well as accountability and clinician acceptance. The governance, explainability and data quality and workflow integration are recent foci on the literature as crucial implementation challenges for primary care (Vidal-Alaball et al., 2024). The potential of using technology and artificial intelligence (AI) to help address the rural-urban divide has also been proposed; but the uptake of these technologies must be sensitive to the local services and infrastructure and workforce limitations (Weeks et al., 2024).

Therefore, a rural PHC federated system needs to be designed to serve as a decision making support system, rather than a general machine-learning service. Use of PHC hardware for local preprocessing, maintaining records within originating organization, encrypting and aggregating model update, and providing predictions as information to complement the risks, rather than a self-contained diagnosis. This design follows a computational architecture and clinical governance.

2.5 Research synthesis and conceptual framework

There are five layers of the conceptual model. Local Multimodal Data Acquisition is the first step. Modality-specific preprocessing and representation learning constitutes the second layer. The third level is "local training" that protects privacy. The fourth layer is secure federated aggregation. The fifth layer is global risk inference, local clinical presentation. The long-term goal is to develop richer multimodal representation for improved predictive discrimination and secure aggregation and

differential privacy to reduce disclosure risk for an acceptable utility price. Heterogeneity-aware optimization should provide a more stable performance in a system, particularly in rural sites.

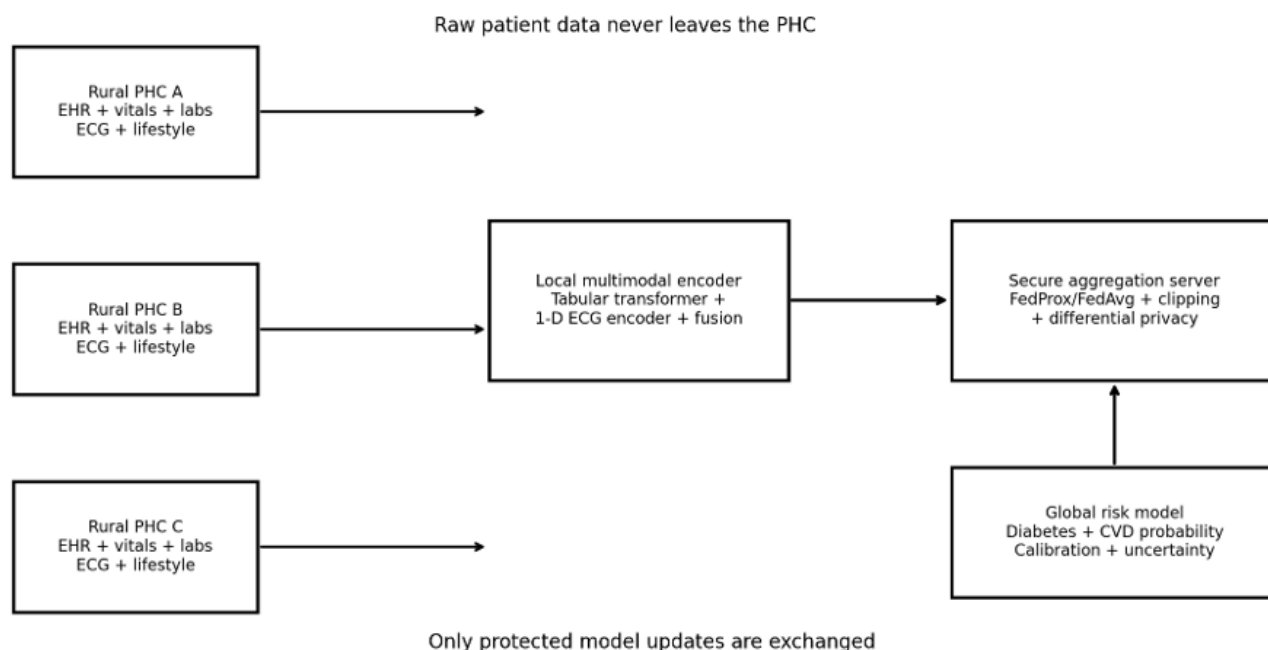


Figure 1. Proposed privacy-preserving multimodal federated architecture for rural PHCs.

3. METHODOLOGY

3.1 Study design

A computational experimental design with simulated distributed rural PHC clients is used in this study. The design of the project to be a future multicentre retrospective validation study, one PHC will have their patient records. The 6 conceptual clients represent the variation in service environments of rural services. The simulation is not intended to be a clinical trial and is not a basis for diagnosis.

Target outcomes are: incident diabetes, and screened diabetes risk and CVD risk within a specified prediction time horizon. The modelling task is two binary classification tasks per disease, each of which has two task-specific prediction heads with a multimodal representation shared by the two tasks. Secondary analysis is a composite high risk state determined for modelling purposes as both target are high risk.

3.2 Data modalities and preprocessing

The EHR modality includes the following information: age, sex, prior diagnoses, medication indicators, family history, BMI, blood pressure and prior utilization. Laboratory results include: fasting glucose or random glucose, available HbA1c, total cholesterol, HDL cholesterol, LDL cholesterol and triglycerides. ECG data shown as a 1D signal, filtered and with fixed length windows. Smoking status, physical activity, dietary factors and sleep-related factors (when recorded) were included as lifestyle factors. For optional retinal or other low cost images, a site with equipment for a fifth modality is utilized.

For continuous variables, training site stats are utilized, while privacy-preserving parameter sharing strategy is used, where individual level stats are not shared. How to deal with missing data: using missingness indicators and locally imputed data. ECG preprocessing consists of baseline correction, amplitude normalization, artifact filtering and resampling. In image-preprocessing, resizing and intensity normalisation (if applicable) are also carried out. Clinically agreed coding or measurement criteria are essential components of a real data implementation of labels and there must be an independent clinical adjudication process for cases with ambiguous labels.

3.3 Multimodal representation model

The local model contains a tabular transformer for EHR and laboratory features, a one-dimensional convolutional encoder for ECG, a compact multilayer encoder for lifestyle variables and an optional convolutional image encoder. The projections of the modalities into a common latent dimension. A gated attention mechanism weights based on modalities and relevance learned. A missing-modality mask stops the missing data from being considered as zero clinical information.

The fused representation is connected to two prediction heads. The probability of diabetes risk is estimated by the diabetes head and the probability of CVD risk is estimated by the CVD head. The multi-task loss is a weighted sum of 2 binary cross entropy losses and regularization loss for calibration. The class weights are computed at the local level, and clipping has been carried out before computing to avoid the presence of extremes in prevalence due to site-specificity.

3.4 Federated optimization

Several local epochs are calculated for each PHC, based on its own private data. Protected parameters (not patient records) are sent to the server. The baseline is FedAvg, and the proposed system suggests a proximal regularization framework coupled with a client-weighted aggregation for mitigating the divergence resulting from non-IID distributions. Client weights are capped in this fashion, so that they don't dominate the global model for a very long time.

The synthetic experiment is repeated 20 times. Depending on the connectivity and availability requirements a subset of the PHCs can participate in each round. Following the aggregation, a global model is redistributed. A held-out PHC is used to assess the ability to generalize the model to another distribution from the one used for model selection (external validation site).

3.5 Privacy protection

It has three levels of privacy. First of all, applying gradients per-client caps the maximal impact of each update. Secondly, the updates to the clipped values are noisy under a differential privacy accountant. Thirdly, aggregation prevents the coordinating server from being able to see the individual server updates. For the synthetic configuration, we set the total budget of privacy epsilon = 3.0 for all the training and the methodological example is set at delta = 1e-5. These parameters have not been designed to be an “optimal clinical privacy setting”.

Compromised client updates and passive network interception are part of threat modelling along with an honest but curious aggregation server. Differential privacy deals with the threat of record-level inference, and secure aggregation reduces the threat of excessive visibility from servers, encrypted transport reduces the threat of unnecessary visibility, and client authentication reduces the threat of unnecessary participation. There is optional support for robust aggregation for Byzantine or poisoned updates.

3.6 Baselines and evaluation metrics

Four models are considered: local-only models (R&D independently per PHC), centralized reference model (constructed by using all the synthetic data), conventional FedAvg and FedProx. The four models are considered as: local-only models (R&D independently per PHC); centralized reference model (constructed by using all the synthetic data); conventional FedAvg and FedProx. The proposed PP-MMFL model consists of Multi-modal Attention, Privacy protection and Heterogeneity-aware aggregation. The accuracy, sensitivity, specificity, precision, F1-score, AUROC and area under the precision-recall curve are used to assess performance. The measures of calibration used are expected calibration error and brier score. Volume of communication, time of the training, client participation and privacy budget are all part of the system evaluation.

In practice, the confidence interval should be computed at the patient or site level for each of the estimands, for resampling purposes, by the bootstrap method. The primary external validation should be done on whole held-out PHCs instead of random records as this splitting might give an optimistic estimate if there are site-specific patterns common to both train and test data sets.

3.7 Ethical and governance considerations

Future empirical study would need institutional ethics clearance, informed consent decision and/or approved waiver, data-protection impact assessment, and site-level data governance agreements. Proposed model for use as a decision support and risk stratification tool only, not for diagnosis or treatment. The explanations should be given at the patient level, covering the most important clinical aspects, but without providing any other patient information. Model updates must be reversible and be

traceable.

4. RESULTS AND ANALYSIS

4.1 Synthetic dataset configuration

For the purposes of demonstration, the simulated federation has 18,000 patient records, with 3,000 patient records in each of the six rural PHCs. The synthetic population has 9,540 records that are identified as low risk and 8,460 records that are identified as being at elevated risk for at least one target condition. The prevalence parameter for diabetes is 31.0% and the prevalence parameter for CVD is 24.0%. The data is deliberately non-IID: there is a wide variety of disease prevalence and disease modalities available for many clients and the distribution of age is variable.

Site	Records	Diabetes risk (%)	CVD risk (%)	ECG availability (%)	Imaging availability (%)
PHC-1	3,000	28.0	20.0	92	18
PHC-2	3,000	34.0	25.0	74	10
PHC-3	3,000	29.0	22.0	88	35
PHC-4	3,000	37.0	29.0	61	5
PHC-5	3,000	31.0	24.0	79	15
PHC-6	3,000	27.0	24.0	68	8

The modality composition used in the simulation is shown in Figure 3. EHR and clinical variables form the largest component, followed by laboratory measurements and ECG signals. Lifestyle variables and optional imaging provide additional information. This composition represents an implementation scenario rather than an empirical estimate of rural PHC data availability.

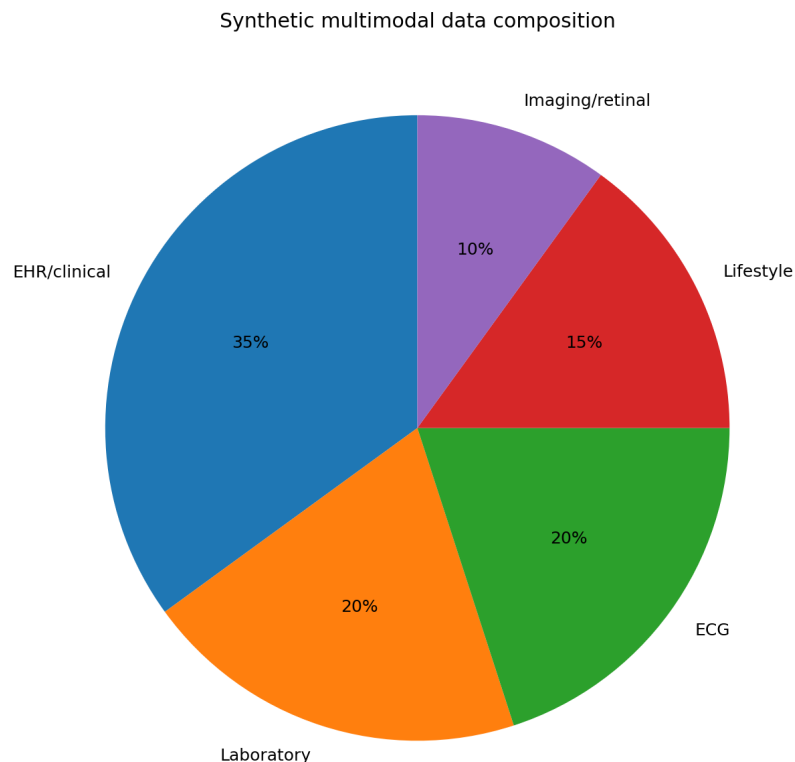


Figure 3. Synthetic multimodal data composition used for methodological demonstration.

4.2 Predictive performance

The synthetic results indicate that the proposed PP-MMFL configuration provides higher simulated discrimination than local-only, FedAvg and FedProx configurations, while remaining below the centralized reference. The result is consistent with the expected trade-off introduced by decentralized learning and privacy protection. The proposed model achieves an AUROC of 0.927, compared with 0.895 for FedAvg and 0.903 for FedProx.

Model	Accuracy	Sensitivity	Specificity	Precision	F1	AUROC	ECE
Local-only	82.1%	78.0%	84.6%	79.2%	78.6%	0.842	0.071
Centralized reference	88.7%	86.2%	90.1%	88.0%	87.1%	0.914	0.028
FedAvg	86.5%	83.9%	88.2%	84.0%	83.9%	0.895	0.046
FedProx	87.3%	85.1%	89.0%	85.4%	85.2%	0.903	0.039
Proposed PP-MMFL	89.4%	87.8%	90.6%	89.0%	88.4%	0.927	0.031

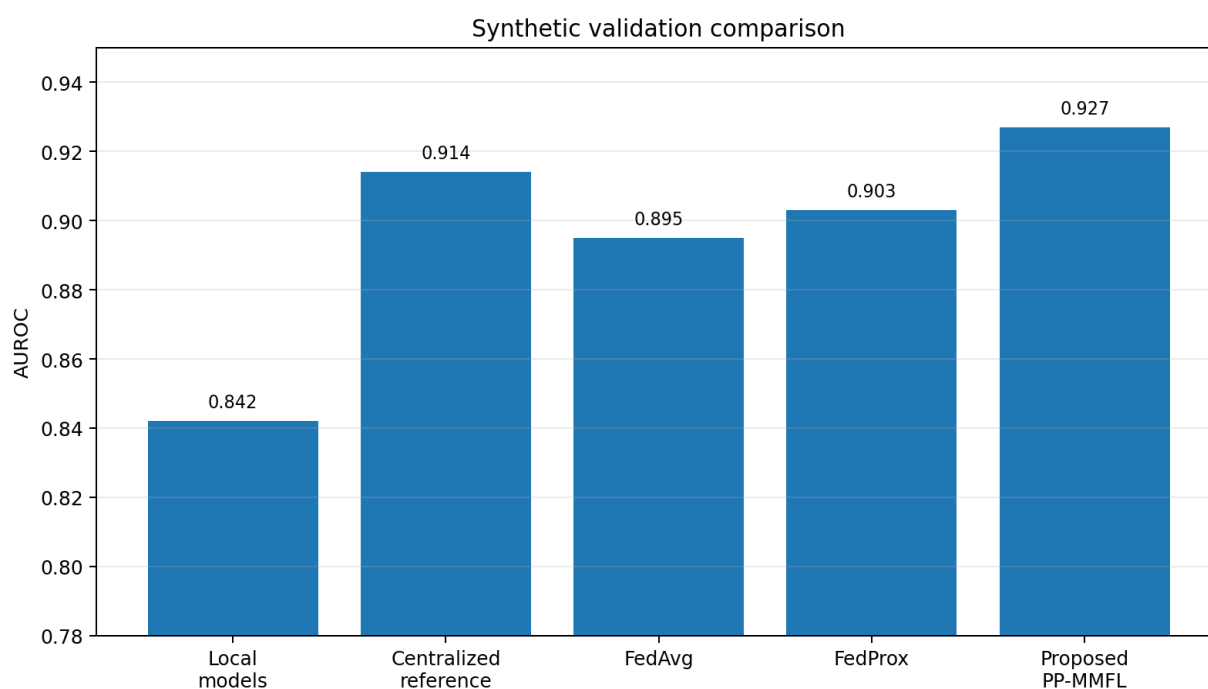


Figure 2. Synthetic AUROC comparison across modelling configurations.

4.3 Disease-specific performance

Outcome	Accuracy	Sensitivity	Specificity	AUROC	Brier score
Diabetes	90.1%	88.9%	90.6%	0.934	0.112
CVD	88.7%	86.5%	90.0%	0.918	0.124
Composite risk	89.4%	87.8%	90.6%	0.927	0.118

The simulated diabetes AUROC is higher than the CVD AUROC, reflecting the stronger availability of structured metabolic predictors in the assumed PHC dataset. The CVD model benefits from ECG features, but ECG availability is incomplete across clients. In a real study, disease-specific performance should be evaluated separately because a high composite score can conceal

weaker performance for one condition.

4.4 Convergence and communication analysis

Figure 4 presents the simulated validation trajectory across 20 communication rounds. The model improves rapidly during the first ten rounds and approaches a plateau thereafter. The pattern illustrates the expected diminishing return from additional communication. In operational settings, an early-stopping rule based on external-site calibration and AUROC could reduce communication burden without relying on training loss alone.

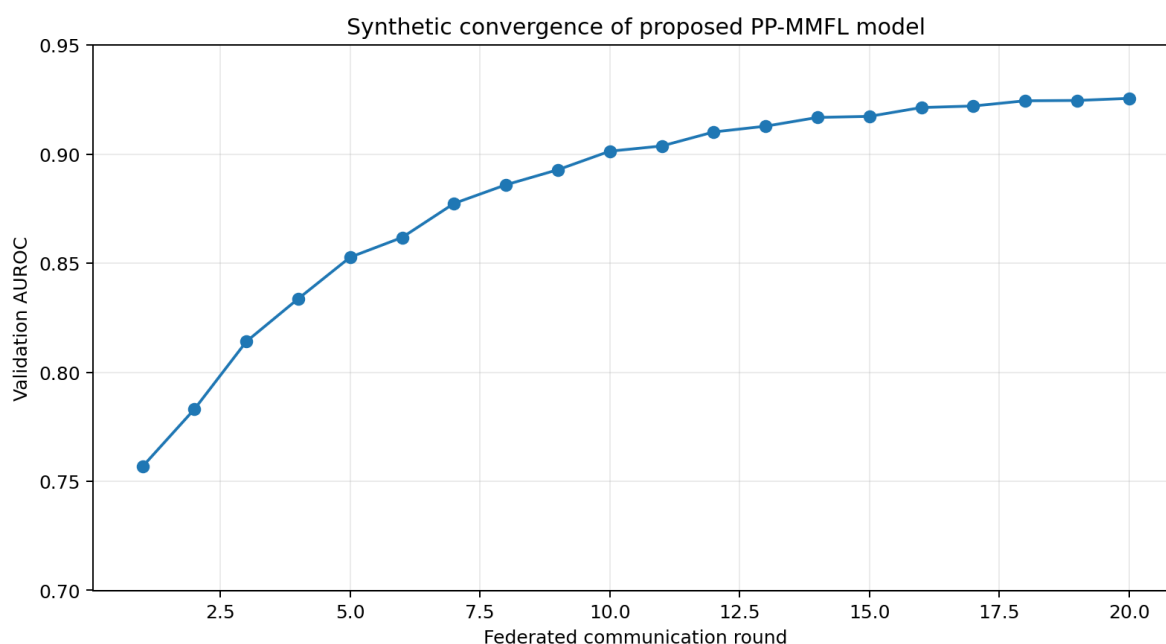


Figure 4. Synthetic convergence of the proposed PP-MMFL model over federated communication rounds.

Configuration	Communication rounds	Relative cost	communication	Privacy protection	Held-out-site AUROC
Local-only	0	1.00		Low	0.842
FedAvg	20	1.00		Moderate	0.895
FedProx	20	1.04		Moderate	0.903
PP-MMFL	20	1.18		High	0.927

The proposed architecture incurs a higher communication cost because multimodal encoders and privacy-related metadata increase update size. The additional cost is the computational price of maintaining a richer shared representation and stronger privacy controls. Compression, partial participation, sparse updates and client-adaptive communication can reduce this burden in future implementation.

4.5 Ablation analysis

Model variant	AUROC	Change from proposed model
EHR only	0.861	-0.066
EHR + laboratory	0.887	-0.040

EHR + laboratory + ECG	0.911	-0.016
All available modalities	0.927	Reference

The synthetic ablation pattern indicates incremental value from adding complementary modalities. The largest improvement occurs when ECG information is added to structured clinical and laboratory variables, while the complete configuration produces the highest simulated AUROC. The result supports multimodal design but does not imply that every rural PHC must possess every modality. The missing-modality mechanism is intended to permit participation by lower-resource sites.

4.6 Privacy-utility analysis

Privacy setting	Synthetic epsilon	AUROC	Accuracy	Interpretation
No DP	Not applicable	0.936	90.2%	Highest utility; weaker formal privacy guarantee
Moderate DP	5.0	0.932	89.9%	Small utility reduction
Proposed DP	3.0	0.927	89.4%	Balanced demonstration setting
Strong DP	1.0	0.902	86.8%	Greater utility reduction

The synthetic privacy-utility curve shows the expected tradeoff between the utility of the prediction and the level of differential privacy. The selection of epsilon should not be based on the model performance as this is not a deployment study. The privacy budget must be determined by a documented threat model, regulatory requirements, institutional risk assessment and expert review of privacy.

5. DISCUSSION

5.1 Interpretation of the framework

The proposed architecture overcomes three interrelated constraints: clinical data fragmentation, privacy constraints, and multi-modal disease-risk prediction. Current healthcare FL evidence indicates that decentralized learning can be used to facilitate collaboration without raw-data pooling but systematic reviews highlight the limited clinical translation (Teo et al., 2024; Li et al., 2025). The present design reacts by making privacy, heterogeneity and operational feasibility as fundamental elements of the system, rather than after-thoughts.

The simulated AUROC gain over conventional FedAvg is comparable to the theoretical effect of modality fusion and heterogeneity-aware optimization. FedAvg also assumes that the local updates are averaged which gives a good approximation to a central objective, however, rural PHCs may have vastly different patient distributions. Local model drift can be mitigated using proximal regularization, and modality-specific information can be considered using attention-based fusion. Recent studies on multimodal and personalized federated healthcare systems (Huang et al., 2024; Al-Dailami et al., 2025) justify these design decisions.

This is important for interpretation as the simulated performance is still below the centralized reference. The idea of federated learning is not to be sold as a guaranteed better solution than centralized learning in terms of predictive performance. Its main use is to allow modelling to be done collaboratively across locality constraints on data. More realistic deployment goals than maximizing discrimination might, then, be performance parity or acceptable performance with stronger privacy.

5.2 Relevance to diabetes and cardiovascular screening

Multiple risk factors and the fact that diabetes and CVD are often co-existent make joint risk prediction a useful tool for supporting primary-care screening. The importance of systematic monitoring of diabetes risk factors, service delivery and outcomes is highlighted in WHO guidance (2024). Early detection and control of modifiable risk factors also play a key role in the prevention of CVD (WHO, 2025). A local PHC model can convert a mix of routine data into a uniform risk output which can trigger confirmatory testing or referral.

The proposed system is not intended to replace the diagnosis of the laboratory, the interpretation of the ECG by qualified

persons or the existing clinical paths. Instead, the model output should be a level of probability or risk category, with uncertainty, and the main contributing variables. Decision-curve analysis and clinical consultation should be used to choose thresholds, not for optimum accuracy.

5.3 Privacy and security implications

This is the difference between federated learning and privacy preserving federated learning. A federated model can be leaky, in the form of gradients and repeated updates or malicious participants. Layered approach would be preferred instead of using a single approach for health care privacy reviews (Aouedi et al., 2023; Ghasemian et al., 2024). This combination is therefore secure aggregation, differential privacy, transport encryption, authentication and audit logging.

There are compromises with the privacy layer as well. Differential privacy can degrade performance and calibration, especially in the case of small client datasets. Secure aggregation can introduce complexity and delay in communication protocol. The homomorphic encryption could offer higher confidentiality but may be very intensive on computing power. The overheads have been reduced in recent encrypted healthcare FL research, but the challenge of resource-constrained rural PHCs to deploy the same is still a significant concern (Rahman et al., 2025).

5.4 Heterogeneity, fairness and rural equity

The data is not just an inconvenience; it is non-IID. When a rural PHC does not have access to ECG or laboratory testing, the model may learn a less informative representation of the data for their patients. Resource disparities can thus turn into algorithmic disparities. The fairness-aware federated-learning research in recent years highlights unequal computational resources as a possible factor causing disparity in collaborative healthcare AI (Ji et al., 2025).

This is proposed to be minimised by the missing-modality mechanism and by client-aware validation, but cannot be removed. Fairness evaluation should provide performance within the following categories: Age, Sex, Socio-economic proxy (where ethically feasible), Geographic site, Modality availability, Disease prevalence. Calibration exercise also needs to be considered at the subgroup level as a globally calibrated model may be miscalibrated for smaller client populations.

5.5 Comparison with recent evidence

Recent research indicates multimodal FL is becoming more and more viable. Cardiac FL has incorporated ECG, imaging, patient records and nutrition data; and ECG-specific research has demonstrated that a federated approach can be used to generalize across institutions without sharing raw signals (Srinivasan et al., 2025; Weimann and Conrad, 2024). There have also been recent efforts related to diabetes and heart-disease prediction that have directly investigated privacy preserving federated architectures (Dash et al., 2025). The studies confirm the feasibility of the direction proposed but vary in the datasets used, the outcomes and in the designs for assessing the studies, and should therefore not be directly considered as benchmarks for the present synthetic experiment, but should rather be used as guidelines for the present study.

There is also a literature gap, which is indicated by the literature. The results of the large systematic review (Teo et al., 2024) showed that most of the healthcare FL studies were technical prototypes and not actual implementations, while the subsequent implementation review study (Li et al., 2025) indicated that methodological flaws, privacy concerns, generalization issues and communication costs are common obstacles. The proposed manuscript therefore considers the prospect of validation, the external testing of the site and operational monitoring as necessary rather than optional add-ons.

5.6 Limitations

The main drawback is that the numerical results are purely synthetic. They illustrate the proposed analysis structure but can not validate clinical accuracy, safety or generalizability. In the real study, patient-level data needs to be obtained from several PHCs, with outcome definitions that are standardized, missingness analysis should be conducted, and clinical adjudication and prospective or temporally separate validation should be performed. Assumed prevalence parameters and availability of modalities are indicative.

The architecture also presupposes the ability of the PHCs to train local models. There might not be enough computing power at certain sites or a reliable connection. Asynchronous federation and edge acceleration might be needed, as might be model compression. The privacy protection itself needs to be validated as it relies on the exact clipping, noise and accounting methods to guarantee formal differential privacy.

The paper does not assess causal effects, clinical outcome, or referral behavior or health-system cost. Future studies should evaluate if screening with models influences the correct diagnosis rate, if it decreases the number of cases missed that have a high risk, if it improves follow-up, and if it is cost effective. Human factors evaluation is also needed to determine the level of clinician comprehension and the appropriate use of probabilistic risk outputs.

6. PROPOSED REAL-WORLD VALIDATION PROTOCOL

6.1 Multicentre recruitment and data governance

An empirical study in the future should target a geographically diversified network of rural PHCs, involving different population sizes, access to digital maturity and access to different modalities. A data-governance agreement should be signed by each site, specifying what variables are allowed, how long data will be kept, who will be responsible for its security, who will be responsible for updating the model, and who will be responsible for responding to incidents. Raw patient records should NOT be transferred to a central coordinating institution.

Development sites, internal validation within participating PHCs and at least one geographically or temporally held-out external site should be included in a minimum validation design. The external site evaluation should be locked prior to final model selection. Reporting should use the proper reporting standards for prediction-models and AI reporting: Participants, predictors, missing data, model training, calibration, subgroup performance and limitations.

6.2 Clinical workflow integration

The interface to be deployed should include a diabetes-risk estimate and CVD-risk estimate, along with a level of confidence or uncertainty, the key contributed variables, and a suggested next clinical action based on locally accepted protocols. The system should provide a record of the version of the model, input completeness and disposition of the clinician without sending unnecessary patient data. Clinical assessment should be the first step in any treatment decision making process, and should be considered before the use of high-risk predictive markers.

6.3 Monitoring and model maintenance

Data drift, calibration drift, subgroup performance, missing-modality rates, false-negative events should be measured during post-deployment monitoring, as should communication failures and privacy incidents. Model updates should be version-controlled and tested in a fixed set of validators in advance of a wide spread rollout of the model. A rollback mechanism should be provided to switch back to the previous validated model if performance (or security) thresholds are not met.

7. CONCLUSION

The proposed multimodal federated learning approach with privacy protection can offer a coherent technical roadmap for collaborating across rural PHCs and locally retaining raw patient-level data for collaborative early prediction of diabetes and CVD. The proposed multimodal representation learning model, attention-based fusion, heterogeneity-aware federated optimization, secure aggregation and differential privacy. The synthetic evaluation shows how to assess predictive performance, calibration and communication cost/privacy parameters simultaneously.

In the methodological demonstration, the synthetic PP-MMFL configuration outperformed both the simulated FedAvg and FedProx baselines, with an AUROC of 0.927, but not as good as the centralized reference. The result shows a realistic privacy utility trade-off and does not provide any evidence of clinical superiority. The multimodal integration did not yield significant improvements in the synthetic ablation analysis and the differential privacy was negatively related to the simulated predictive utility.

The next research phase should involve actual (held-out-site validated) multi-centre PHC data, clinical outcome adjudication, suitability for subgroups, calibration assessment, privacy auditing and prospective workflow assessment, for translation into rural primary care. One of the key strengths of the proposed framework is that the learning is data-local, meaning it is possible to conduct collaborative learning in less centralized environments, without losing the separation between the algorithmic risk prediction and clinical diagnosis.

DECLARATIONS

Data availability

No patient-level dataset was supplied for this manuscript. The numerical experiment is synthetic and is included solely to demonstrate the proposed evaluation framework.

Ethics approval

No human participants were enrolled for the synthetic methodological demonstration. A future empirical implementation would require institutional ethics approval and appropriate data-governance authorization.

Conflict of interest

No conflict of interest is declared for the methodological manuscript.

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