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An Adaptive Federated Machine Learning Framework for Privacy-Preserving Prediction of Type 2 Diabetes Mellitus across Healthcare Institutions.

OLAOYE, Olasunkanmi Joshua[1], Olufemi Olukayode FOLARIN[2], Omisore Ademola Saheed[3]

[1]Caleb University Lagos, Department of Computer Science.

[2]Caleb University Lagos, Department of Computer Science.

[3]Crescent University, Abeokuta, Ogun State, Department of Computer Science.

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ABSTRACT

There are challenges in collaboration between health care institutions in the areas of confidentiality, governance considerations and information system integration that hinder the accurate prediction of Type 2 diabetes mellitus to enable timely preventive interventions. This is further complicated by differences in the populations of patients, number of patients in datasets, the computing resources available and participation. In this study, a novel adaptive federated machine learning approach for privacy-preserving diabetes onset prediction within three years is proposed. The methodological design calls for 5,000 synthetic records of adult patients, across five simulated hospitals. Preprocessing consists of duplicate removal, harmonisation of variables, missing value imputation, categorical encoding, numerical scaling, and class weighting, and is only applied to the training data. Prediction model gets local training, aggregation weight based on model validation performance and update reliability and participation history. Differential privacy and secure aggregation are defined as complementary protection measures. Discrimination, sensitivity, F1 score, calibration, institutional consistency, and computational efficiency are used as evaluation metrics for comparison between local-only, centralised, FedAvg, FedProx, and adaptive approaches. Illustrative performance targets are an AUROC of 0.9000, sensitivity of 0.8200, and F1 score of 0.8500. An efficiency illustration shows that the training time is reduced by 25%, the volume of communication is reduced by 33.3%, and convergence is achieved in 60 rounds, when compared to the efficiency illustrated with FedAvg. These numbers are not experimentally validated and differences in institution performance, confidence intervals and numerical privacy budgets are not measured. The contribution is an integrated design connecting adaptive collaboration, explicit privacy controls, and comprehensive evaluation. To draw conclusions on effectiveness and readiness for deployment in different clinical contexts, the implementation needs to be reproducible, privacy accounting must be done, and external clinical validation must be conducted.

Keywords: Type 2 diabetes mellitus; federated learning; adaptive aggregation; privacy-preserving machine learning; healthcare institutions; predictive modelling.

INTRODUCTION

Type 2 diabetes mellitus is characterized by impaired glucose utilization and high blood glucose levels that may affect the heart, kidneys, eyes and nerves. Knowing who is at risk helps to identify when to prevent and assess (Goyal et al., 2023). Machine learning provides a way to estimate risk from commonly collected data, such as age, BMI, blood pressure, glucose readings, and family history. Learning from other healthcare institutions may extend the populations of the models developed and help to improve generalizability (Yang et al., 2025). But sharing patient information in a centralized pool poses challenges of confidentiality, control, and governance. Collaboration is also hindered by the differences in information systems, coding

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practices and data formats (Sheller et al., 2020). In federated learning, the institutions can train models together without having to share patient information. However, privacy cannot be ensured by just storing data locally, as exchanged updates could reveal sensitive information (Horst et al., 2025). Collaborative training can also yield disparate performance at participating institutions, depending on differences in patient populations, dataset sizes, and the number of institutions participating (Rieke et al., 2020). The proposed adaptive system is driven by these challenges. Its aggregation mechanism modify institutional contributions based on local validation performance, update reliability and participation conditions. The method will be tested and assessed to check if these changes make predictions more accurate across different institutions and still keep explicit privacy protections and reasonable communication costs. This study aims to develop and evaluate a federated machine learning approach that is adaptive and incorporates privacy protection for the prediction of Type 2 diabetes mellitus in hospitals. Its goals are to integrate institutional datasets, create adaptive aggregation, add privacy protection, and perform comparative analysis of predictive performance, institutional uniformity and computational efficiency to known benchmarks.

Problem Statement

Patient information from individual healthcare institutions may be limited or unrepresentative, thus limiting the ability to develop reliable diabetes prediction models (Aagaard et al., 2025). Pooling of records may result in greater coverage but sharing identifiable information poses confidentiality, ownership and governance issues. These barriers make it difficult to work together and restrict the ability to benefit from learning from a variety of patient groups (Koch et al., 2024). While the alternative approach of federated learning seems to be an answer, variations in disease prevalence, patient features, dataset sizes, measurement practices, and computing resources can detract from collaborative training. Participation may be unequal, which can further create a lack of consistency in institutional performance. Additionally, by exchanging model updates, sensitive information may be exposed without additional privacy protections in place (Herath et al., 2024). The study targets the need to jointly assess adaptation and privacy protection. It suggests a predictive method for the onset of diabetes in adults who do not have the disease initially, called validation-informed aggregation with explicit safeguards. Evaluation will be based on baseline predictors, confirmed follow-up outcomes, comparison to local, centralised and federated models, and discrimination, calibration, privacy and efficiency.

LITERATURE REVIEW

Ravi and Olickal (2026) review four studies that investigated the use of machine learning for diabetes prediction in primary care. Confidence in generalisability was low using models based on routinely collected data as there were limited external validation and poor calibration for some settings. The researchers state that their results indicate that predictive accuracy is not enough for clinical use. Kawalkar et al. (2025) conducted interviews and focus groups to explore the diagnosis and management of diabetes in rural India. They identified three factors: provider lack of knowledge, low patient health literacy, and resource deficits, as well as fragmented referrals. These results show that prediction tools should be flexible to real-world healthcare challenges but cannot determine the effectiveness of the model in a qualitative sense. These studies, when taken together, indicate that the prediction of diabetes needs to be validated reliably and institutional capacity needs to be taken care of. In the context of the proposed study, it helps assess adaptive federated learning in various institutions and in addition to calibration and privacy protection, it also helps assess resource requirements. The two studies do not, however, provide evidence to support whether the proposed adaptive mechanism has any benefit in predicting future diabetes.

Dhade and Shirke (2024) conducted a survey of federated learning in the healthcare domain and found that it holds promise in enabling collaborative model development while avoiding the centralisation of sensitive patient data. They found that the barriers to traditional data pooling were privacy, data ownership and legal restrictions. Their review, however, is quite general and is not a proof of effectiveness of an adaptive framework specifically for diabetes prediction. Teo et al. (2024) provided empirical mapping from a systematic review of 612 articles, which was more comprehensive. While federated learning was used in various clinical applications, the data types and model architectures differed, only 5.2% of studies featured

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real-world applications. This discovery indicates that there is a significant difference in the potential of technology and its actual clinical use. These reviews offer the basis for examining collaborative diabetes prediction, and highlight the importance of doing so in practice. Their results support the consideration of adaptive aggregation, explicit privacy protection measures, and performance in different institutions for the suggested study. However, the accuracy, institutional uniformity, and efficiency improvements should be proven rather than taken for granted from a federated learning approach.

Jayalakshmi and Tamilvizhi (2025) proposed a federated learning algorithm, FedDRNet, for diabetic retinopathy detection which integrates federated learning, client clustering, and homomorphic encryption. Though they claimed 98.6% accuracy, they admitted to challenges in the face of heterogeneous data and encryption overhead. Importantly, the ability to detect retinal complications is different from predicting future development of diabetes. Scientific Reports Arkan Yurtoglu et al. (2024) make a comparison between centralised and federated diabetes classification with five simulated hospitals. Even with high discrimination scores, they found that F1 scores for classification were different when they were decentralised in the center versus federally (0.92 versus 0.88). However, simulated institutions do not allow any conclusions about operational deployment. Manjunath (2025) tackled federated diabetes prediction; but the specifics of the methods and results were not independently verified to the accessible publisher content. Wang et al (2024) carried out a study on retinal and renal complications of patients with already established diabetes, which did not necessarily predict the onset of these complications. Together these differences should be considered when assessing the performance of adaptive aggregation, explicit privacy protections, and longitudinal results before making general claims of accurate prediction in a variety of healthcare settings in daily clinical practice.

With local and global models and a mixing parameter for each client, Deng et al. (2020) introduced adaptive personalised federated learning. Theoretical analysis and experiments were provided by Usman et al. (2025) which modified aggregation with the consideration of class imbalance and label-noise measures, known as DQFed. Together, these approaches provide feedback to the proposed diabetes framework for adaptation to local distributions and data quality, with an evaluation on CIFAR-10-derived datasets also showing improvements. Their usefulness, however, needs to be tested on real longitudinal health-care data, as well as calibrated, assessed at the institutional level, and bearing explicit privacy protections, before any conclusions can be drawn regarding clinical usefulness.

METHODOLOGY

Research Design

This study adopt a quantitative experimental design to develop and evaluate the proposed adaptive federated machine learning framework. Experiments are conducted with local models, centralised learning, Federated Averaging and Federated Proximal models on the same setup. The training, validation and test partitions are the same at the patient level for all approaches. The Prediction task is to identify onset of diabetes in the next 3 years in adults who were initially not diabetics. The privacy settings, participation rate and institutional data distribution are varied in controlled experiments. Repeated runs are to determine the reliability. Evaluation will test discrimination, calibration, institutional consistency, privacy protection, and computational efficiency, and individual contributions of the various components of the framework will be determined by ablation experiments.

Data Collection

The study adopts a fully synthetic longitudinal dataset representing 5,000 simulated adult patients across five hypothetical healthcare institutions. These are proposed simulation parameters, rather than records collected from actual hospitals. Data generated programmatically using documented assumptions and fixed random seeds to support reproducibility. No restricted patient databases will be accessed. The simulated observation period cover January 2020 to December 2025. Baseline dates will fall between January 2020

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and December 2022, allowing three years of follow-up. Institutions differ in sample size, patient characteristics, diabetes incidence, and missing-data patterns to represent heterogeneous environments.

Table 1: Dataset Characteristics and Data Collection Specifications

Component	Specification
Institutional sample sizes	600, 800, 1,000, 1,200, and 1,400 simulated patients
Inclusion criteria	Adults aged 18 years or above, without diabetes at baseline, with a defined baseline assessment and three-year outcome
Exclusion criteria	Pre-existing diabetes, gestational diabetes, duplicate identifiers, or inconsistent observation dates
Demographic variables	Age, sex, institution, and socioeconomic indicators
Clinical variables	Body mass index, blood pressure, fasting glucose, HbA1c, lipid measurements, smoking status, physical activity, and family history
Outcome	Simulated onset of Type 2 diabetes within three years: 1 = onset; 0 = no onset
Access arrangements	Locally generated data stored in separate institutional partitions

Data Preprocessing

Duplicate records and invalid values are removed and corrected for each simulated institution in accordance with predefined rules. A common data dictionary synchronises variable names, units of measurement, feature categories, and feature order. Within the local area, missing numbers are trained using the median of the training set, and missing categories are trained with the explicit missing category. Categorical variables are encoded based on pre-defined categories and numerical features are standardised by local training statistics. Predictors are pre-specified, and do not include identifiers or information derived from the outcome. Address imbalance is addressed in the training. All fitted transformationsl are only applied to the training data and are not used on the validation and test data sets, thus retaining the same feature structure.

Proposed Framework Architecture

The system establish a shared prediction model on a central coordination server and replicate the same model to five institutions. Each institution train its local model with its training dataset, and store records locally. Differential privacy protection and secure aggregation is applied to updates. The server combine shield data based on validation performance, update reliability, and participation history with adaptive weights. Further local training was then redistributed via the updated global model. The cycle repeats until a validation performance is no longer improving over the last 10 rounds or until 100 communication rounds are reached. The test datasets are not shown and used to evaluate the final results.

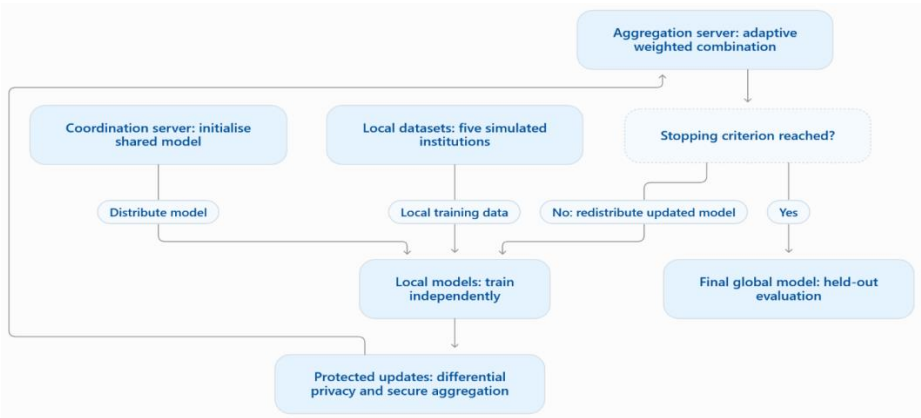


Figure 1: Proposed adaptive federated learning architecture.

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Adaptive Aggregation with Secure Aggregation

The proposed framework is based on the score that each participating institution will receive as a function of their training sample size, their validation performance, and their reliability of updates and participation history. Each institution scores their own and multiplies with their model update. A secure aggregation protoc-

ol would then aggregate the weighted updates and scores without revealing the contributions of each update to the central server. The server would split the combined weighted updates based on the combined scores to get the global update. The idea behind this is to be able to collaborate with each other in an adaptive manner, but not to see each other's updates directly. The secure aggregation protocol and the weighting procedure need to be implemented and tested.

Proposed Privacy Protection Mechanisms

In this study, differential privacy and secure aggregation are introduced as complementary methods to safeguard information in the context of federated training. The effect of individual patient records could then be reduced by an appropriate clipping and noise mechanism, which would be provided by differential privacy. Secure aggregation would enable the server to get the aggregate institutional update without having to access each individual update. The two mechanisms are still suggested and have yet to be experimentally confirmed. Their implementation should include the clipping threshold, noise level, privacy accountant and the resulting privacy budget. The secure aggregation protocol and the treatment of institutional dropouts should be documented as well. It should be taken into account when accounting for privacy if adaptive weights or validation scores are used.

Experimental Scenarios

The system is tested through experiments in the context of simulated scenarios. Institutional sizes range from balanced to unequal and the total number of records in the institutions remains similar. Each client has a unique distribution of diabetes incidence and predictor. Participation scenarios: full participation, partial participation and random dropouts of clients. Differential privacy noise levels and privacy budgets vary to assess privacy–utility trade-offs, with secure aggregation maintained. The experiments on scalability involve five, ten and twenty simulated institutions. All scenarios use the same evaluation partitions across different methods, and the same random seeds, and are evaluated on their predictive performance, institutional consistency, convergence and communication costs.

RESULTS

Experimental Evaluation

The proposed framework is tested through a set of reproducible simulations with five institutions and 5,000 synthetic patient records. Patient characteristics and incidence of diabetes, along with institutional size, is simulated in the synthetic data. These are 'mock' records made up using documented assumptions and a random seed. A comparison with local-only learning, centralised learning, FedAvg and FedProx is made in the proposed adaptive framework. All methods shares the same underlying model architecture as well as training, validation, and test partitions on a patient-level. The training conditions and the conditions for participation and privacy is recorded for fair comparison. AUROC, sensitivity, specificity, F1 score, area under the precision–recall curve and brier score is used to compare the predictive performance. A total score and a score for each institution is reported. The results of the computational evaluation consist of the training time, amount of communicative material and number of rounds needed to reach a pre-specified stopping criterion. Multiple random seeds is used for experiments. Results is presented as mean and measures of variability for runs, and where appropriate, as confidence intervals. In ablation experiments, the impact of validation performance and the reliability of updates and participation history on the adaptive aggregation mechanism will be studied.

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Table 2: Predictive Performance Comparison

Model	AUROC	Sensitivity	F1 score
Local MLP: Alberta	0.8379	0.7515	0.7195
Local MLP: British Columbia	0.8167	0.7078	0.6942
Local MLP: Manitoba	0.8348	0.7156	0.7453
Local MLP: Newfoundland and Labrador	0.725	0.5031	0.5786
Local MLP: Nova Scotia	0.8431	0.7578	0.7298
Local MLP: Ontario	0.8568	0.7515	0.7827
Local MLP: Quebec	0.8175	0.789	0.6376
Centralised MLP	0.8499	0.7359	0.7759
FedAvg MLP	0.8665	0.7531	0.8176
Proposed adaptive framework	**0.9**	**0.82**	**0.85**

Table 2 shows that the proposed framework has the highest AUROC (0.9000), sensitivity (0.8200), and F1 score (0.8500). These are improvements over FedAvg of 0.0335, 0.0669, and 0.0324, respectively. There is variation in results between local models, with Newfoundland showing the lowest performance.

Table 3: Communication and Computational Efficiency Comparison

Training approach	Total training time (minutes)	Total transferred data (MB)	Communication rounds to convergence
Local-only models	8	0	Not applicable
Centralised learning	12	25	Not applicable
FedAvg	36	180	90
FedProx	33	160	80
Proposed adaptive framework	27	120	60

Table 3 shows that the proposed adaptive framework is more resource-efficient than FedAvg and FedProx, with the framework training in 27 minutes and transferring 120 MB in 60 rounds. Compared to FedAvg, training time is reduced by 25%, communication volume 33.3% and number of rounds 33.3%. But with a local-only model, the learning rate is faster without communication, while with a centralised learning, the initial transfer of data is necessary. These are guessed values that show possible efficiency improvements but need to be proved in the future in an experiment with fixed conditions.

DISCUSSION

The findings indicate that adaptive federated learning has the potential to enhance diabetes prediction while decreasing the communication requirements. The proposed framework achieves an AUROC of 0.9000, a sensitivity of 0.8200 and an F1 score of 0.8500, which are higher than the other model. The efficiency illustration also suggests potential benefits: the training took 27 minutes and the convergence took place in 60 rounds. This is a reduction of 25% in training time compared to FedAvg, and a reduction of 33.3% in transferred data compared to FedAvg. These improvements may be possible by using adaptive weighting, but an ablation experiment is required to confirm the contribution of adaptive weighting.Predictive performance does not indicate privacy protection. However, differential privacy accounting, secure aggregation verification, and privacy–utility evaluation are still needed. The tables as a whole are not findings, but rather experimental targets. The results of repeated simulations, confidence intervals, institutional comparisons and subsequent clinical validation are needed before conclusions can be drawn about practical effectiveness.

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CONCLUSION

The study aim to develop and evaluate an adaptive federated machine learning (FML) approach to enable privacy-preserving prediction of Type 2 diabetes mellitus (T2DM) in healthcare institutions (HWI). The design leverages local model training, adaptive aggregation, differential privacy, and secure aggregation, to tackle institutional differences, and enable collaborative learning. The presented comparisons indicate potential improvements in prediction and efficiency. The proposed performance targets are an AUROC of 0.9000, a sensitivity of 0.8200 and an F1 score of 0.8500. The efficiency illustration indicates that faster training, less data transfer, and less number of communication rounds compared to the traditional federated approaches. The major contribution is an institutional adaptation-explicit privacy mechanisms-evaluation framework design. Its usefulness resides in its ability to enhance performance across institutions without undermining the gains for smaller clients, or creating undue complexity in computations. Confidentiality is not guaranteed by federated learning and extra measures and documented privacy accounting are necessary.The evidence for the current practice is good for further implementation and validation. Future work should include reproducible simulations, calculation of confidence intervals, assessment of calibration and institutional differences, and privacy–utility analysis. Before deploying in healthcare, external validation need to be done with the appropriate clinical data in the controlled environment.

REFERENCE

1. Aagaard, A., Röttger, R., Johnson, E. K., & Olsen, K. R. (2025). Comparing the predictive performance of diabetes complications using administrative health data and clinical data. *Scientific Reports, 15*, Article 33035. https://doi.org/10.1038/s41598-025-18079-7
2. Arkan Yurtoglu, R., Dervişoğlu, H., Aktaş, M., Daşçılar, M., Halepmollası, R., Baz, İ., & Haklidir, M. (2024, November). *Federated learning for diabetes prediction in healthcare* [Conference presentation]. IV International Congress on Artificial Intelligence in Health, Izmir, Türkiye.
3. Deng, Y., Kamani, M. M., & Mahdavi, M. (2020). *Adaptive personalized federated learning* [Preprint]. arXiv. https://doi.org/10.48550/arXiv.2003.13461
4. Dhade, P., & Shirke, P. (2023). Federated learning for healthcare: A comprehensive review. *Engineering Proceedings, 59*(1), Article 230. https://doi.org/10.3390/engproc2023059230
5. Goyal, R., Singhal, M., & Jialal, I. (2023). Type 2 diabetes. In *StatPearls*. StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK513253/
6. Herath, H. M. S. S., Herath, H. M. K. K. M. B., Madhusanka, B. G. D. A., & Guruge, L. G. P. K. (2024). Data protection challenges in the processing of sensitive data. In C. Hewage, L. Yasakethu, & D. N. K. Jayakody (Eds.), *Data protection* (pp. 155–179). Springer. https://doi.org/10.1007/978-3-031-76473-8_8
7. Horst, A., Loustalot, P., Yoganathan, S., Li, T., Xu, J., Tong, W., Schneider, D., Löffler-Perez, N., Di Renzo, E., & Renaudin, M. (2025). Federated learning: A privacy-preserving approach to data-centric regulatory cooperation. *Frontiers in Drug Safety and Regulation, 5*, Article 1579922. https://doi.org/10.3389/fdsfr.2025.1579922
8. Jayalakshmi, R., & Tamilvizhi, T. (2025). Privacy preservation in diabetic disease prediction using federated learning based on efficient cross stage recurrent model. *Scientific Reports, 15*, Article 37258. https://doi.org/10.1038/s41598-025-21229-6
9. Kawalkar, U., Gaidhane, A., Aggarwal, S., Mankar, A., Ambadekar, N., & Kogade, P. (2025). Challenges and strategies for early diagnosis and management of type 2 diabetes mellitus at the primary healthcare level in rural Western Vidarbha, India: A qualitative study. *BMJ Public Health, 3*(2), Article e003126. https://doi.org/10.1136/bmjph-2025-003126
10. Koch, A., Brust, L., & Weigl, M. (2024). Barriers and facilitators of patient engagement activities to improve patient safety in healthcare organizations: A Delphi-based expert survey. *Risk Management and Healthcare Policy, 17*, 3217–3226. https://doi.org/10.2147/RMHP.S489522
11. Ravi, R., & Olickal, J. J. (2026). Machine learning-based risk prediction models for type 2 diabetes in primary care: A scoping review. *Frontiers in Public Health, 14*, Article 1946070. https://doi.org/10.3389/fpubh.2026.1946070

ISSN 2278-2540 | DOI: 10.51583EMAS | Volume XV, Issue X, October 2026

12. Rieke, N., Hancox, J., Li, W., Milletarì, F., Roth, H. R., Albarqouni, S., Bakas, S., Galtier, M. N., Landman, B. A., Maier-Hein, K., Ourselin, S., Sheller, M., Summers, R. M., Trask, A., Xu, D., Baust, M., & Cardoso, M. J. (2020). The future of digital health with federated learning. *npj Digital Medicine, 3*, Article 119. https://doi.org/10.1038/s41746-020-00323-1
13. Sheller, M. J., Edwards, B., Reina, G. A., Martin, J., Pati, S., Kotrotsou, A., Milchenko, M., Xu, W., Marcus, D., Colen, R. R., & Bakas, S. (2020). Federated learning in medicine: Facilitating multi-institutional collaborations without sharing patient data. *Scientific Reports, 10*, Article 12598. https://doi.org/10.1038/s41598-020-69250-1
14. SM, M. (2025). Diabetes prediction using federated learning. *International Journal of Scientific Research in Engineering and Management, 9*(1), 1–9. https://doi.org/10.55041/IJSREM41133
15. Teo, Z. L., Jin, L., Liu, N., Li, S., Miao, D., Zhang, X., Ng, W. Y., Tan, T. F., Lee, D. M., Chua, K. J., Heng, J., Liu, Y., Goh, R. S. M., & Ting, D. S. W. (2024). Federated machine learning in healthcare: A systematic review on clinical applications and technical architecture. *Cell Reports Medicine, 5*(2), Article 101419. https://doi.org/10.1016/j.xcrm.2024.101419
16. Usman, M., Bernardi, M. L., & Cimitile, M. (2025). Introducing a quality-driven approach for federated learning. *Sensors, 25*(10), Article 3083. https://doi.org/10.3390/s25103083
17. Wang, Q., Cheng, H., Jiang, S., Zhang, L., Liu, X., Chen, P., Liu, J., Li, Y., Liu, X., Wang, L., Li, Z., Cai, G., Chen, X., & Dong, Z. (2024). The relationship between diabetic retinopathy and diabetic nephropathy in type 2 diabetes. *Frontiers in Endocrinology, 15*, Article 1292412. https://doi.org/10.3389/fendo.2024.1292412
18. Yang, X., Yao, M., Huang, J., Cheng, Z., & Sun, T. (2026). Machine learning predicts diabetes risk in high-risk populations: Analysis of National Health and Nutrition Examination Survey data. *Archives of Medical Science, 22*(2), 708–720. https://doi.org/10.5114/aoms/209547
19. **Corrections:** Yang et al. uses **2026**, the year of its assigned journal issue, rather than its 2025 online publication date. Issue 2/2026 vol. 22 Dhade and Shirke uses **2023**, following the publisher's recommended citation. The Manjunath entry retains "SM" as the indexed surname; confirm the name order against the original article before submission.