FEDERATED INTELLIGENCE FOR PRIVACY IN HEALTHCARE

Deshpande Sreeja[1]
MTech [1]

Dr.V.Ananthakrishna[2]
Professor[2]

Dr. U.Srilakshmi[3]
Professor & HOD[3]

Department of Computer Science and Engineering[1234]
Sridevi Women's Engineering College,Gopanpally, Hyderabad, Telangana,India[1234]

***Abstract*— Data-driven models are becoming more and more important in mental health care, but protecting the privacy of private patient data is still a huge problem. The decentralized training of models through a FL approach has emerged as an intriguing method. However, due to various challenges such as data type issues, non-uniform contact information, and potential security concerns arising from parameter swapping, it is not without its drawbacks. This paper shows a HFL system for mental health applications that protects privacy. It combines CFL and QFL. The CFL method places the clients into groups where they share a similar weight change, to enhance the performance of the model. This enables you to train locally and aggregate efficiently. Along with this, QFL uses a Variational Quantum Classifier (VQC) and angle encoding to prepare the quantum state, which takes advantage of the benefits of quantum computing to make classification better. The system is tested with independent and non-independent data distribution to see how robust the system is in real world scenarios. Experimental results indicate that QFL is more accurate and recall than regular FL, and that CFL is more precise and good at communicating. The proposed framework addresses issues such as privacy, scalability, and speed well, providing a robust solution for the detection of stress during real-time in a mental health system that includes wearable technology.**

"Keywords— Hybrid Federated Learning, Mental Healthcare, Clustered Federated Learning, Quantum Federated Learning, Variational Quantum Classifier, Privacy Preservation, Data Heterogeneity, Wearable IoT."

I. INTRODUCTION

Mental health care is now an important field that requires rapid diagnosis and monitoring, and thus needs more technologies to assist them. Combining artificial intelligence with data-driven methods has made it much easier to figure out complicated patterns in behavior and bodily processes. But, because mental health information is confidential, there are significant privacy concerns, making it difficult to share data and block the development of robust and generic models. In the new decentralized way, FL enables people to collaborate to train models without sharing raw data. This ensures the privacy of the user when accessing the data sources which are distributed [1].

FL has been created over the last few years to enable mixed and multimodal healthcare information. This can ease the integration of different sensor inputs into smart healthcare systems, so that a more accurate forecasting can be achieved [2]. The hybrid encryption methods have been enhanced, especially in federated and clustered systems that provide increased protection to data. These solutions enable secure communication and secure data sharing when training and aggregating [3]. Besides, there are novel designs using blockchain and quantum-key cryptography introduced to attain safety and scalability in distributed health care systems, especially in smart cities [4]. Others that are being considered include quantum inspired models (either non-perturbative or perturbative) for enhancing disease prediction tasks with strict privacy constraints [5] and differential privacy techniques to improve disease prediction tasks with strict privacy constraints.

Federated Learning systems have been broadly studied in Mental Health to evaluate their therapeutic relevance, efficacy and protection of privacy features [6]. The combination of quantum computing and federated learning has created new opportunities to process enormous datasets and to speed up computer processing as proven in recent comprehensive studies on Quantum Federated Learning (QFL) [7]. Furthermore, recent works have demonstrated that the quantum computing and FL can be adapted to allow secure and distributed quantum model training, which can be used to enhance privacy and scalability [8]. There's also growing interest in hybrid models that bridge both the older models of AI and newer models of quantum AI. They are especially beneficial for IoT applications in the healthcare and cybersecurity sectors [9].

Smart healthcare systems combining privacy with integration of various learning styles within a federated system are offered by hybrid federated systems like MedShieldFL. In addition, the theory and practical development of QFL is yet to be studied. Its potential impact on privacy-preserving ML and the ease of computer use are of particular interest to them, and how it facilitates privacy-preserving ML without compromising data security [11].

The primary goal is to create a privacy-preserving clustered and quantum hybrid federated learning framework that improves the accuracy of the model, security of data transmission, communication costs and performance of real-time monitoring of mental health status from distributed wearable data.

II. RELATED WORK

Recent breakthroughs in privacy-preserving ML have a significant impact on the application of FL in IoT and healthcare scenarios. The integration of smart learning

methodologies and advanced security mechanisms has recently received great attention from researchers to address the challenges of conventional centralized systems.The researchers are now trying to address the drawbacks of the traditional centralized solutions by shifting the emphasis towards the integration of smart learning approaches with robust security features. For instance, Sundaramurthy, Kathavarayan, et al. [12] investigated the problem of quantum secured federated learning in 6G-assisted IoT threat detection system. They are looking to make data more private and less susceptible to advanced cyber threats by employing quantum cryptography. The importance of quantum security in Distributed Systems can be clearly seen.

Meena, Raghavender et al. [13] developed a shared learning strategy for maintaining privacy using XAI approaches for mental health treatment. They value their privacy and their choice of models. This will enable better decisions for clinicians and prevent data silos from developing on the sensitive mental health data. Likewise, Fiaz, Kanwal et al. [14] gave a detailed review of Federated and cloud-based methods for predicting mental health issues. Despite these efforts, challenges arose such as data inconsistencies, data size limitation and privacy concerns, which made it difficult to use in real life situations.

A more useful advanced computer model with additional features is even more useful in the federated learning system. Ben Othman and Ali [15] developed a quantum-entangled neuro-symbolic swarm federation model for healthcare applications based on IoMT. They mix quantum computing with swarm intelligence, symbolic reasoning and more to create a faster way to process multimodal data without too much privacy infringement. Concurrently, Islam and Ullah, inc. [16] introduced an adaptive federated learning system for user-centric Internet of Medical Things (IoMT) systems. The system emphasizes data sharing, and dynamically adjusts models to fit the large and wide-ranging data.

There are several contributions to the broader field of privacy preserving machine learning by Zaman, Gauravaram et al. [17] who offered a comprehensive discussion of several diverse fields such as federated learning, differential privacy and safe computing technologies. They point out that a suite of measures is needed for sustainable and resilient solutions, and that privacy should be maintained. Apart from this, very few researchers like Naresh et al. [18] examined the secure multiparty computation approaches in healthcare as well its role in training the models together without revealing the private patient information.

There have also been a lot of new studies on ethics and justice in federated learning. Ali, Abbas, Mir, et al. [19] addressed ethical considerations related to the adoption of federated learning in healthcare, focusing on topics such as data privacy, mitigating bias, and ensuring fair access to AI-driven medical services. Their results highlight the need for measures to ensure privacy and fairness and transparency in decision-making.

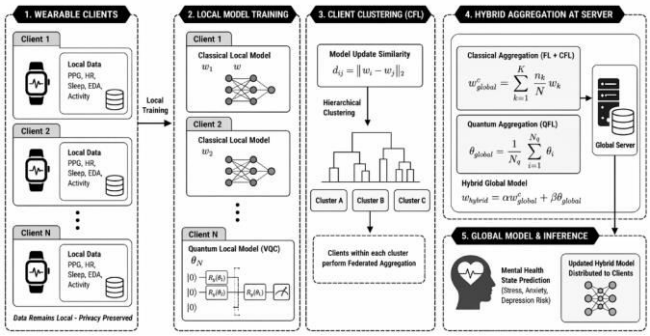
One interesting area of research is the combination of quantum computing and federated learning. Gupta et al., Mathur et al. The article [20] explored the advantages and cons of employing quantum computing together with collaborative learning in particular about its capabilities of enhancing the calculation speed and its capacity to handle huge and complicated sets of data. Similarly, Okolo, Arowogbadamu, et al. [21] studied federated learning for mobile data analytics and found that the privacy protection is effective for users, while the edge device shares the information without a centralized model.

Liang, Chen et al. [22] also went into the depth of evaluation federated learning for collaborative research across hospitals and highlighted some of the most serious problems with the system, including the need for extra communication and the variety of data types, as well as the ability to scale up the system. They show the need of designing efficient algorithms capable of learning from data and adapting to the environment on the fly to boost the performance of models in globally distributed medical applications.

A lot of progress has been made with privacy-preserving federated learning, particularly in combination with quantum computing, secure communication protocols and adaptive learning approaches. But problems like computational complexity, communication efficiency, heterogeneity of data, and ethical issues are still open study questions. This means that stronger and more hybrid frameworks need to be made for real-world healthcare applications.

III. Materials And Methods

The proposed system is based on creating a HFL structure that protects privacy and combines advanced learning paradigms for quick analysis of mental health data from multiple sources. The system implements Federated Learning to train the model at local devices with private user data. The framework incorporates scalable federated architectures which are well suited to the big data context to enhance the management of large volumes of data and distributed analytics. This makes it easier to have several clients collaborate without compromising privacy [23]. In order to circumvent the challenges from the traditional FL, the authors incorporate a clustered learning mechanism that clusters clients by their model weight updates, which is achieved by using hierarchical clustering algorithms. This Clustered Federated Learning method offers enhanced localized training, reduces connection expenses, and simplifies model personalisation. A quantum-inspired learning component is also built in to improve the way features are represented and how anomalies can be found using joint neural client models. This provides a more reliable system in case of complex healthcare data [24]. In addition, there is a Quantum Federated Learning feature of the system, where a quantum state is prepared using a Variational Quantum Classifier (VQC) and angle encoding. The method is a combination between the quantum and classic theories, and allows for more accurate classification of data, and makes it easier to analyse multimodal data, in healthcare settings, etc. [25].



"Fig.1 System Architecture"

The hybrid federated learning architecture, in which the data from wearable sensors are leveraged to predict a person's mental health state, is illustrated in Fig. 1. Wearable Clients collect local biological data to start the process. Then, local model training is done with both the classical and variational quantum circuits (VQC). Third, Client Clustering (CFL) clusters clients according to the similarity of their model updates. Then, the Global Server performs Hybrid Aggregation, a hybrid of traditional and quantum weights. Finally, the new hybridized model is transported to various locations and risks for stress and anxiety are calculated in real time.

A) Data Collection and Preprocessing:

The system takes advantage of a multimodal healthcare dataset comprising data from wearable IoT devices that capture physiological and behavioral elements. Some of the most commonly used of these signs are ECG, EDA, body temperature, respiration, and movement-based attributes. The data from the wearable sensors is often noisy and inconsistent, thus the pre-processing is a crucial step to ensure the quality and reliability of the data. Initially, the missing numbers are dealt with by using interpolation and statistical imputation. The data are smoothed and noise removed using filtering techniques such as moving average filters and low-pass filters.

All the input variables are transformed to the same range (typically 0 to 1) using normalization methods. This simplifies feature scaling, and reduces the time required for training. Then, feature picking is done to cut down on the number of dimensions and the amount of work that needs to be done. Two algorithms which are used in figuring out the importance scores of features are RF and ET Classifier. The most important features are retained. This reduces redundancy and improves the model's performance.

After being processed, the dataset is split into several subsets that relate to different clients in a federated environment. The idea is that one can model real-life situations using independent data sets, as well as non-independent sets. This will ensure the system is resilient, scalable and robust across a variety of device types and configurations.

B) Federated Learning Framework:

It is based on the decentralized Federated Learning system, which enables multiple client devices to collectively learn a global model without sending their raw data. Every client creates a local model, inputs information from a central server. Local training is done using optimization methods such as Adam optimizer and binary cross-entropy as the loss function. Training is performed locally, only changes in the model's weights are sent to the central computer. This means that your privacy is protected.

The Federated Averaging (FedAvg) method is used by the server to combine these updates. It calculates the weighted average of all of the client models to create a new global model. This is repeated many times through a number of transmission turns until convergence is achieved. While keeping model accuracy high, the structure is made to cut down on communication costs as much as possible.

Adaptive learning rates and dynamic client participation methods are used to deal with different types of data. Many situations make it easier to use the global model since different clients add different things to it. Secure aggregation techniques also are employed to ensure that model updates are safe during delivery. This makes sure that sensitive information can't be figured out from shared parameters, even if the communication lines are broken into. This simplifies the system, making it overall safer and more private.

C) Clustered Federated Learning Mechanism:

The method is designed to be efficient and addresses the issue of the diversity of the clients, and is implemented as a CFL system. Users are put into groups called clusters based on how alike their model updates are. This is performed by the hierarchical clustering. At initially, all clients conduct normal federated training to get new weights. Then these updates are observed to find similarity measures e.g. Euclidean distance which is basis of clustering.

Agglomerative hierarchical clustering is an iterative process in which similar customers are grouped. This forms a dendrogram which indicates hierarchical linkages. After the groups have been formed, each group is given a federated model to train. This will tailor learning. This reduces the impact of non-IID data and improves the accuracy of the model by working on similar sets of clients.

Each cluster has its own aggregating processes. The models from the several clusters obtained are then regularly merged to keep the global model updated. This classification decreases communication cost and speeds up the convergence. Furthermore, clustering is a cost efficient technique, as the optimal learning parameters for clients whose features are correlated could be shared by a number of clients. This is much more scalable and ensures successful model training in a hospital environment comprising a wide variety of patient types.

D) Quantum Federated Learning Integration:

A Quantum Federated Learning (QFL) part of the method is added to make computations even faster and the models more useful. Angle encoding methods are used to turn classical data into quantum states. Here each feature is correlated to an angle of rotation in the quantum circuits. This encoding makes it possible to easily store data with a lot of dimensions in a quantum state space.

A Variational Quantum Classifier (VQC) is used as the local model by each client. The VQC consists of a multitude of layers of quantum gates and entanglement processes in parameterized quantum circuits. The best values of these parameters are obtained by solving a minimization problem using a classical optimization technique such as the gradient descent. This model is hybrid quantum and classical, and can extract complex patterns from data that are difficult to explain classically.

Once the local training is done, the improved quantum parameters are sent to the central server. There, it aggregates in a similar fashion to classical federated learning. The new global quantum model is then returned to the clients which can then be used to retrain with the quantum model. Despite the increased computational resources required, QFL has advantages such as improved feature modeling, enhanced learning abilities, and improved privacy. This combination makes the system more robust and capable of safely and effectively dealing with complex healthcare data.

E) Hybrid Federated Learning Model Integration:

The proposed approach is based on a model called HFL which combines the best of the traditional FL, CFL, and QFL. This hybrid approach is intended to overcome issues such as data inconsistencies, redundant contacts, and restricted learning in individual models.

Initially, the system is similar to any other FL system, with various clients training local models on their private data and pushing changes to the models to a central server. To enhance this process, a clustering method is added. The clients are assigned to clusters using a hierarchical clustering algorithm, where the clients within a cluster have similar model weight updates. Each cluster performs some federated training and thus personalization is improved and the impact of non-IID data is reduced.

Concurrently, some classic classifiers are replaced with a VQC in order to add the quantum learning part. Angle encoding provides a way to represent data as quantum states, thus allowing the efficient representation of features of many dimensions. These quantum models are trained locally and the parameters of these models are updated to the traditional models.

Lastly, a hybrid aggregation strategy is used on the server. The strategy includes changing the cluster level and using the quantum model parameters to produce a robust global model. This unified framework provides improved accuracy, enhanced privacy protection and quicker communication. This makes it appropriate for real-time mental health apps, distributed wearable data.

IV. Experimental Results

Suggested Hybrid Federated Learning framework performance is assessed using different metrics including accuracy, precision, recall and F1-score with the independent and non-independent data. The results demonstrate that the federated approach has good data privacy protection and high classification performance. Clustered learning will enhance accuracy by having models locally trained on similar clients. This reduces the impact of the use of various data types and increases the trustworthiness of the models.

Thanks to quantum technology, it can remember things and discover difficult patterns in extremely large healthcare data sets. Quantum circuit variability causes initial changes to be seen during early communication rounds. However, the model stabilizes and gets consistent performance with fewer iterations than traditional methods. The clustered approach also accelerates the convergence and decreases the amount of work the communication needs to do, due to the fact that unnecessary global updates are limited.

A comparison test confirms that the hybrid system is more efficient and reliable than traditional federated approach. The quantum part, however, is more complex with more likely elaborate calculations that may require improved hardware support. In conclusion, the results demonstrate that clustering and quantum techniques are suitable in a federated environment. This provides mental health application with a favorable privacy, accuracy, and scalability.

Accuracy: How well a test can tell the difference between sick and healthy people is called its accuracy. It is good to determine the percentage of the cases that are true positive and true negative to get some sense of how accurate a test is. As far as math is concerned, this can be expressed as

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} (1)$$

Precision: Precision is the percentage of correct classification of cases or samples for which the cases are correctly classified as positive. So, here is the way to determine the precision:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)$$

Recall: Recall is a metric in ML which indicates the percentage of important instances of a particular class that are correctly identified by a model. It displays model coverage of an instance of a given class. It is measured as correct positive/true positive (TP).

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} \ + \ \mathrm{FN}} (3)$$

F1-Score: F1 score is a measure to evaluate the accuracy of a ML algorithm. It adds together a model's accuracy and recall scores. The accuracy measure is the number of correctly predicted values for all the data points.

$$F1\ Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100 (4)$$

Table.1 Performance Evaluation

Model	Accuracy	Precision	Recall	F1-Score
Traditional Federated Learning	91.20	90.85	89.70	90.25
Clustered Federated Learning	93.75	94.10	91.95	93.01
Quantum Federated	94.60	92.80	95.30	94.03

Learning				
Hybrid FL (CFL + QFL Proposed)	96.15	95.40	96.80	96.09

The performance of the FL, CFL, QFL and Hybrid FL models are compared in Table 1. It demonstrates that, overall, the Hybrid FL model is more accurate, and uses more fair evaluation criteria.

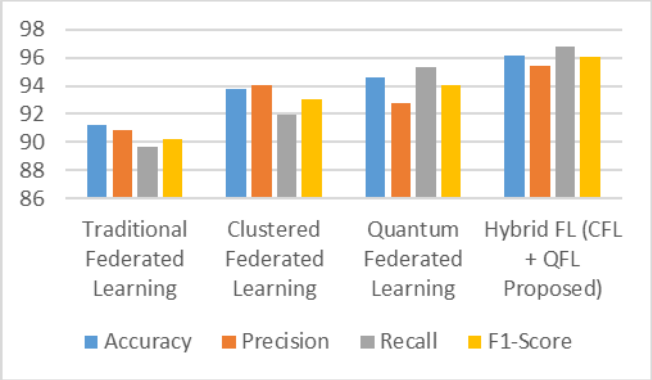


Fig.2 Comparison Graph

As illustrated in Fig. 2, the proposed Hybrid FL model outperforms the standard FL model, clustered FL model and quantum FL model on all the tests.

V. Conclusion

The framework is hybridized with clustered and quantum-enhanced federated learning to demonstrate a viable approach for mental health analysis while maintaining privacy. The combination of both decentralized learning and clustering techniques is easier to handle various data types. This results in improved personalization of the model and reduces communication overhead. If the addition of quantum-based learning to the system improves the system's efficacy in identifying complex trends in large quantities of physiological data, then it also improves the efficacy of the system in prediction. The hybrid learning method does not have a single indicator that is most important, but instead has found a better balance between accuracy, precision, recall and F1-score than the individual ones, thereby improving overall performance. Ensures that user data remains secure on local devices while allowing users to train models as a group. The system can also adapt to real-world scenarios, like non-uniform data patterns that are typical in environments with wearers of the devices, e.g., healthcare settings. It is easily converged and scalable, allowing it to easily be applied on a large scale to many distributed systems in the healthcare sector. Despite the increased complexity of computations, the advantages of improved learning and privacy protection outweigh the disadvantages of the quantum part. Combining clustering with quantum approach in federated learning may yield robust, secure, and intelligent mental health solutions of the future.

In the future, progress can be made by combining lightweight optimization methods to make computations simpler, especially in quantum-enhanced models, which will make them work on devices with limited resources. Adaptive clustering techniques can be used to dynamically change groups of clients on the fly in response to changes in data trends. Further sophisticated privacy techniques such as differential privacy and homomorphic encryption can further ensure the safety of data. For real-time deployment, edge computing, or low latency communication methods can be included. The framework can be extended to support multimodal and cross domain healthcare information for the sake of generalization improvement. Finally, AI approaches that are explainable can help create models that are more transparent, fostering greater trust and understanding where significant healthcare decisions are made.

References

[1] Tanbhir, G., & Shahriyar, M. F. (2025, February). Quantum-inspired privacy-preserving federated learning framework for secure dementia classification. In *2025 International Conference on Electrical, Computer and Communication Engineering (ECCE)* (pp. 1-6). IEEE.

[2] Wang, J., Quasim, M. T., & Yi, B. (2025). Privacy-preserving heterogeneous multi-modal sensor data fusion via federated learning for smart healthcare. *Information Fusion*, *120*, 103084.

[3] Srivenkateswaran, C., Jaya Mabel Rani, A., Senthil Kumaran, R., & Vinston Raja, R. (2025). Securing healthcare data: A federated learning framework with hybrid encryption in cluster environments. *Technology and Health Care*, *33*(3), 1232-1257.

[4] Samantray, B. S., & Reddy, K. H. K. (2025). A Federated Learning Approach Towards Hybrid Blockchain, Quantum-Key-Encryption based Distributed System: A Futuristic Healthcare Architecture for Smart Cities. *Blockchain: Research and Applications*, 100385.

[5] Pandey, S., Gupta, S., Gupta, P., & Verma, A. (2025, June). Quantum-Inspired Neural Networks, Federated Learning with Differential Privacy, and Hyperdimensional Computing for Enhanced Heart Disease Prediction. In *International Conference on Data Analytics & Management* (pp. 273-287). Cham: Springer Nature Switzerland.

[6] Hadke, P., & Patil, S. (2025, October). Federated Learning Architectures for Mental Health Data: A Systematic Review of Privacy-Preserving Approaches and Clinical Efficacy. In *2025 International Conference on Sustainable Communication Networks and Application (ICSCN)* (pp. 1916-1923). IEEE.

[7] Uddin, M. R., Shaon, S., Rahman, R., Nguyen, D. C., Dobre, O. A., & Niyato, D. (2025). Quantum Federated Learning: A Comprehensive Survey. *IEEE Communications Surveys & Tutorials*, *28*, 3942-3975.

[8] chander Mashetty, P., Chittipothu, S., Gangabathula, N. V., Gangabathula, S., Gutta, P. K., & Rajalakshmi, N. A. S. (2025, July). Federated Learning in Quantum Computing for Privacy-Preserving and Distributed Quantum Model Training. In *2025 6th International Conference on Data Intelligence and Cognitive Informatics (ICDICI)* (pp. 1537-1544). IEEE.

[9] Kumar, A., Kiran, S., & Kumar, R. S. (2025). Hybrid Quantum-Classical Frameworks for IoT Security: Bridging AI, Federated Learning, and Cybersecurity. *Journal Publication of International Research for Engineering and Management*, *10*(3).

[10] Murala, D. K., Krishna, G. S., Kiran, T. V. S., & Mohamud, A. K. (2025). MedShieldFL-a privacy-preserving hybrid federated learning framework for intelligent healthcare systems. *Scientific Reports*, *15*(1), 43144.

[11] Nguyen, D. C., Uddin, M. R., Shaon, S., Rahman, R., Dobre, O., & Niyato, D. (2025). Quantum federated learning: A comprehensive survey. *arXiv preprint arXiv:2508.15998*.

[12] Sundaramurthy, A., Kathavarayan, R., Raju, K. K., Dayalan, S. P., Mohan, J., & Sivakolundu, V. P. (2025). Quantum-Secured Federated Learning for Privacy-Preserving and Adaptive Attack Detection in 6G IoT. In *Secure Communication for the 6G and the Internet of Things Networks* (pp. 253-276). CRC Press.

[13] Meena, V., Raghavender, G., Jayakar, S., & Kumar, J. S. (2025, July). Privacy-Focused Federated Learning for Mental Health Data with XAI Techniques. In *2025 6th International Conference on Data Intelligence and Cognitive Informatics (ICDICI)* (pp. 1338-1343). IEEE.

[14] Fiaz, I., Kanwal, N., & Al-Said Ahmad, A. (2025). A Systematic Review of Federated and Cloud Computing Approaches for Predicting Mental Health Risks. *Sensors*, *26*(1), 229.

[15] Ben Othman, S., & Ali, O. (2025). Quantum-entangled neuro-symbolic swarm federation for privacy-preserving IoMT-driven multimodal healthcare: SB Othman, O. Ali. *Scientific Reports*.

[16] Islam, U., Ullah, H., Khan, N., Ahmad, I., & Saleem, K. (2025). Adaptive Federated Learning Framework for Privacy-Preserving Consumer-Centric IoMT: A Novel Secure Data Collaboration Model. *IEEE Transactions on Consumer Electronics*.

[17] Zaman, Z., Gauravaram, P., Hassan, M., Jha, S., & Hu, W. (2026). Privacy-Preserving Machine Learning for IoT: A Cross-Paradigm Survey and Future Roadmap. *arXiv preprint arXiv:2603.13570*.

[18] Naresh, V. S., Venkata Raju, A., & Srinivasa Rao, O. (2025). Secure Multiparty Computation for Privacy-Preserving Machine Learning in Healthcare: A Comprehensive Survey. *Wiley Interdisciplinary Reviews: Computational Statistics*, *17*(3), e70046.

[19] Mir, B. A., Abbas, S. R., & Lee, S. W. (2026, January). Federated Learning in Healthcare Ethics: A Systematic Review of Privacy-Preserving and Equitable Medical AI. In *Healthcare* (Vol. 14, No. 3, p. 306). MDPI.

[20] Mathur, A., Gupta, A., & Das, S. K. (2025). When federated learning meets quantum computing: Survey and research opportunities. *IEEE Communications Surveys & Tutorials*, *28*, 1351-1380.

[21] Okolo, J. N., Arowogbadamu, A. A. G., Adeniji, S. A., & Tasie, R. K. (2025). Federated learning for privacy-preserving data analytics in mobile applications. *World Journal of Advanced Research and Reviews*, *26*(01), 1220-1232.

[22] Liang, P., Chen, J., Yu, H., Huang, H., & Pu, B. (2025). Federated Learning for Cross-Hospital Collaborative Research: A Comprehensive Survey of Applications, Challenges, and Future Directions. *Challenges, and Future Directions (August 01, 2025)*.

[23] Dawood, A. G., & Turki, E. M. (2026). Federated Learning for Privacy-Preserving Big Data Analytics in Distributed Systems: Federated Learning for Privacy-Preserving Big Data Analytics in Distributed Systems. *JOINCS (Journal of Informatics, Network, and Computer Science)*, *9*(1), 11-23.

[24] Godavarthi, D., Rekapalli, V. C. S., Mohanty, S., Jaswanth, J. V., Polisetty, D., Dash, B. B., & Moreira, F. (2025). Federated quantum-inspired anomaly detection using collaborative neural clients. *Frontiers in artificial intelligence*, *8*, 1648609.

[25] Harikrishna, T. (2025, November). Quantum-Enhanced Federated Learning with Explainable Multimodal Intelligence for Heart Disease Risk Stratification, Progression Analysis, and Personalized Care. In *2025 9th International Conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 858-868). IEEE.