Assessing the Novelty and Publishability of FEDMED Research

Based on the search results and current literature, I have evaluated your research "FEDMED: A Privacy-Preserving Adaptive Federated Learning Framework for Smoker Prediction with Robustness Against Data Quality Variations" for novelty and publishability in IEEE.

Current State of the Art

Several related approaches exist in the current literature:

- Quality-aware federated learning exists with focuses on label denoising games and price of stability analysis[1]
- FedLN framework addresses label noise across different FL training stages[2]
- FedNolowe uses normalized loss-based weighted aggregation for improving global model stability[3]
- Various robust aggregation approaches have been proposed for federated learning[4]
- Multiple implementations combining homomorphic encryption with federated learning exist[5] [6] [7] [8]

Your Novel Contributions

Your research offers several distinct innovations:

1. The integration of privacy-preserving quality metrics (1/local loss) with homomorphic encryption specifically for encrypted model aggregation
2. MAD-based robust score aggregation as an effective defense against dishonest score reporting, which proved superior to percentile-based clipping
3. Comprehensive evaluation demonstrating resilience against both noisy clients and adversarial attacks within the same framework
4. Application to healthcare domain (smoker prediction) with implications for privacy-sensitive medical data

Assessment of Publishability

The comprehensive experimental framework you've developed appears methodologically sound, with:

- Clear baseline comparisons
- Systematic evaluation of different noise and adversary percentages

- Thorough ablation studies of different clipping mechanisms
- Concrete metrics showing performance benefits

Conclusion

Yes, your research appears novel and publishable in IEEE.

The unique combination of quality-aware aggregation using 1/loss metrics, MAD-based robust score protection, and homomorphic encryption creates a distinctive contribution not present in current literature. The thorough empirical evaluation further strengthens your publication case.

I recommend proceeding with paper preparation for IEEE submission, emphasizing the robust score aggregation mechanism as your primary contribution, since this element appears most novel compared to existing work.

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1. paste.txt
2. https://arxiv.org/pdf/2310.08790.pdf
3. https://arxiv.org/abs/2208.09378
4. https://www.biorxiv.org/content/10.1101/2025.03.30.646222v1
5. https://slogix.in/machine-learning/robust-aggregation-for-federated-learning/
6. https://research.ibm.com/blog/federated-learning-homomorphic-encryption
7. https://arxiv.org/abs/2505.02409
8. https://arxiv.org/abs/2104.06824