Enhancing Privacy Protection by Applying Federated Learning to AI-assisted STI/HIV Risk Prediction Models

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Background:
The prediction of sexually transmitted infections (STI), including HIV, is a crucial aspect of public health as early detection/treatment can markedly improve patient outcomes and prevention. Federated Learning can provide an effective solution for collecting/analysing large amounts of patient data without compromising privacy. Training prediction models locally on individual user devices keeps sensitive medical data confidential and protected from unauthorised access. The aim of this study was to examine feasibility, acceptability, and limitations of utilising Federated Learning for predicting risk of STI/HIV among men who have sex with men (MSM).

Methods:
Data from the Demographic and Health Surveys (DHS) Program, encompassing data gathered from multiple countries, were preprocessed to identify the optimal set of predictors for the model. Initially, a model was trained locally on each country's data. Data were then aggregated and used to update a global model. The performance of the global model was compared to local models. We tested the performance of our proposed method using data from eight countries.

Results:
Results obtained from the global model were found to be superior to those from both the local model and the model constructed using centralized DHS data. Specifically, the Random Forest Federated Learning method demonstrated an accuracy of 93.3%, while the local model reached 92.2%. In contrast, the model built using centralized DHS data had lower accuracy (86%). Challenges/obstacles are highlighted regarding the research process, particularly in data collection, cleaning, mining, and model building.

Conclusion:
Our proof-of-concept study demonstrates superiority of a global model regarding performance and highlights potential benefits of using an innovative method in AI-assisted STI/HIV prediction—while preserving privacy. Findings have implications for public health by providing a novel tool for predicting STI/HIV—despite inherent challenges in building the tool. Furthermore, findings highlight the

significance/benefits of incorporating privacy-preserving techniques in AI healthcare applications.

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None

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