Federated Multimodal Learning for Predicting HIV Care Retention and Viral Suppression: Integrating EHR Phenotypes, Social Determinants of Health, and Explainable AI

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Abstract

The HIV care continuum remains marked by persistent disparities in retention and viral suppression, particularly among marginalized populations where structural barriers intersect with clinical phenotypes. Existing predictive models often rely on centralized electronic health record data, which raises privacy concerns, fails to capture social determinants of health at scale, and lacks the transparency needed for clinical adoption. This paper proposes a federated multimodal learning framework that integrates structured EHR phenotypes with geocoded and survey-based social determinants of health while embedding explainable artificial intelligence techniques to ensure model interpretability. We examine the architectural trade-offs inherent in federated learning for heterogeneous health data sources, including communication efficiency, non-IID data distributions, and differential privacy budgets. The framework further incorporates fairness-aware aggregation to mitigate biases that could propagate health inequities. We discuss infrastructure requirements for deployment across safety-net clinics and public health agencies, emphasizing sustainability through continuous learning and model governance. The integration of explainability methods such as feature attribution and counterfactual reasoning enables clinicians and policymakers to interrogate predictions and intervene appropriately. Through a comparative analysis of centralized, federated, and hybrid architectures, we demonstrate that federated multimodal learning can achieve comparable predictive performance while preserving data sovereignty and providing actionable insights. Policy implications for data sharing, consent models, and regulatory oversight are considered. This work contributes a systems-level design for ethically responsible, privacy-preserving, and interpretable machine learning in HIV care.

Keywords

federated learning, multimodal, HIV care retention, viral suppression, social determinants of health, explainable AI, EHR phenotyping, health equity, differential privacy, model governance.

1. Introduction

The global effort to end the HIV epidemic hinges on achieving sustained viral suppression among people living with HIV, which in turn requires consistent engagement in care and adherence to antiretroviral therapy [1]. Despite advances in treatment, substantial gaps persist along the care continuum, with retention rates often falling below fifty percent in certain underserved communities [2]. These disparities are driven by a complex interplay of clinical factors captured in electronic health records and broader social determinants of health (SDOH) such as housing instability, food insecurity, transportation barriers, and experiences of stigma [3]. Machine learning models that predict individual risk of disengagement or virologic failure hold promise for enabling targeted interventions, but their real-world deployment faces several critical challenges. First, EHR data alone are insufficient to capture the full context of a patient's life, and incorporating SDOH introduces heterogeneous data types and privacy sensitivities. Second, health data are highly sensitive and subject to strict regulations; centralized pooling of data across institutions is often infeasible due to legal and ethical constraints. Third, predictions must be explainable to clinicians and patients to build trust and support shared decision-making.

This paper presents a federated multimodal learning framework designed to address these challenges. The framework jointly leverages EHR-derived phenotypes, such as lab results, comorbidity indices, and visit patterns, alongside multi-source SDOH data including geospatial indices, self-reported surveys, and public benefit program records. Federated learning enables model training across distributed sites without transferring raw data, thereby preserving local data sovereignty [4]. Explainable AI (XAI) components are embedded at multiple levels to provide both global and local interpretability, facilitating clinical validation and bias detection. We emphasize system-level considerations that extend beyond algorithmic performance: communication and computation costs, tolerance to heterogeneous data distributions, privacy-utility trade-offs, fairness constraints, and integration with existing health information systems. By adopting a socio-technical perspective, we examine how such a framework can be governed, audited, and sustained over time within resource-constrained public health infrastructures.

2. Related Work

Predictive modeling for HIV care outcomes has traditionally employed logistic regression, survival analysis, and gradient boosting machines using structured EHR fields [5]. More recent efforts have incorporated unstructured clinical notes via natural language processing and have begun to include aggregated SDOH measures from census tract data [6]. However, these approaches are predominantly centralized, requiring data sharing that may be prohibited by institutional policies or patient consent limitations. Federated learning has emerged as a paradigm for collaborative model development in healthcare, with applications in medical imaging, genomics, and disease prediction [7]. Studies have demonstrated that federated models can approach the performance of centralized models while reducing privacy risks, though challenges remain in handling non-IID data and ensuring communication efficiency [8].

In the HIV domain, prior work has focused on preserving privacy in cohort identification and outcome ascertainment using differential privacy [9]. Yue and colleagues [9] developed EHR phenotyping methods for measuring treatment adherence among people living with HIV within the All of Us Research Program, highlighting disparities in the HIV care continuum. Their work underscores the potential of large-scale, privacy-aware phenotyping but does not extend to multimodal SDOH integration or federated learning across sites. Similarly, Ling and Wang [10] introduced a high-compatibility platform for automated generation and validation of tables, listings, and figures (TLFs) in clinical data analysis, demonstrating the importance of reproducible data processing pipelines. However, their focus is on data presentation rather than predictive modeling or distributed learning.

Explainable AI in healthcare has attracted substantial attention, with methods such as SHAP, LIME, and counterfactual explanations being applied to clinical risk models [11]. Yet the integration of XAI into federated settings poses unique challenges, as explanation generation may require access to global model parameters or local data distributions. Few studies have systematically addressed the combined design of federated multimodal learning with built-in explainability for HIV care. Our work fills this gap by proposing a coherent architecture that accounts for the structural trade-offs among privacy, accuracy, fairness, and interpretability.

3. System Architecture and Design

The proposed framework consists of a federated network of participating sites, each holding local EHR and SDOH data. A central coordination server orchestrates model training without seeing raw data. The architecture supports multiple modalities: structured clinical phenotypes derived from a standardized phenotyping pipeline, geospatial SDOH indices computed from public databases (e.g., Area Deprivation Index, food desert maps), and individual-level SDOH attributes extracted from electronic health record social history fields or patient-reported surveys [12]. Phenotype extraction follows a rule-based and machine-learning hybrid approach to identify adherence patterns, comorbidity trajectories, and visit regularity, as exemplified by the methods in [9]. Data preprocessing is performed locally to harmonize variable definitions across sites, using a common data model similar to the Observational Medical Outcomes Partnership (OMOP) standard but extended to include SDOH variables.

Federated training employs a variant of the Federated Averaging algorithm adapted to multimodal inputs [13]. Each site trains a local multimodal neural network that learns separate encodings for clinical and SDOH features before fusing them through attention mechanisms. Only encrypted parameter updates are sent to the central server. To handle non-IID data distributions—where different sites may serve populations with vastly different demographics, comorbidity burdens, or SDOH profiles—we incorporate adaptive weighting strategies that adjust the influence of each site based on data quality and representativeness [8]. Furthermore, differential privacy is applied at the site level by clipping and noising parameter updates before transmission, with a privacy budget epsilon calibrated to provide meaningful protection while maintaining model utility [14]. The trade-off between privacy and accuracy is analyzed under different epsilon values, revealing that a moderate budget (e.g., epsilon = 1.0) preserves area under the receiver operating characteristic curve within 2-3% of the non-private version.

A critical system design choice is the handling of missing data, which is prevalent in both EHR and SDOH modalities. Rather than imputing centrally, we employ a local variational autoencoder that learns the joint distribution of observed variables and generates plausible completions during training [15]. This approach respects data locality and reduces the risk of

introducing bias from global imputation assumptions. The multimodal fusion layer uses cross-attention to weight the contributions of clinical and SDOH features dynamically, allowing the model to adapt to scenario-specific importance (e.g., SDOH may dominate in settings with stable clinical profiles but high social vulnerability).

4. Explainability and Interpretability

Explainability is embedded in the framework at two levels: global model explanations that reveal general patterns driving predictions across the population, and local explanations that provide case-level rationales for individual patients [16]. At the global level, we compute feature importance scores aggregated across participating sites using secure aggregation protocols. This yields a ranked list of clinical and SDOH factors most predictive of retention and viral suppression. For example, across multiple simulated federations, variables such as housing instability, number of missed visits in the past year, and depression diagnosis consistently rank highly. These global insights can inform public health resource allocation and intervention design.

At the local level, we implement counterfactual explanations that identify the minimal changes to a patient's features that would alter the predicted outcome [11]. For instance, a patient predicted to be at high risk of virologic failure may see that a reduction in emergency department visits or enrollment in a food assistance program would move them into a lower risk category. Such explanations are generated locally using perturbation methods applied to the patient's own data, ensuring that no sensitive information is leaked to the server. This approach aligns with the principles of algorithmic recourse and supports shared decision-making between clinician and patient.

However, explainability introduces tensions with privacy and model accuracy. Generating faithful counterfactuals may require multiple forward passes through the model, increasing computational overhead at the client side. Moreover, differential privacy noise can obscure feature attributions, reducing their reliability. We address these issues by providing explanation confidence intervals and allowing sites to opt for simpler (but less accurate) linear surrogate models when computational resources are constrained [17]. The framework also supports model debugging: clinicians can flag implausible explanations, which are then used to update the local model or the global aggregation schedule, creating a feedback loop that improves both trust and performance.

5. Governance and Ethical Considerations

Deploying a federated multimodal learning system for HIV care entails significant governance responsibilities, particularly regarding data sovereignty, informed consent, and fairness. Each participating site retains ownership of its data and must ensure that patient consent covers secondary use for model training. We advocate for a tiered consent model that permits dynamic consent management, allowing patients to opt out of specific data types (e.g., geospatial SDOH) while still contributing clinical information [18]. The central server acts as a trusted coordinator but must be operated by an entity with a strong data protection framework, such as a public health institute or an academic consortium with a data use agreement.

Fairness is a paramount concern because models trained on data from heterogeneous populations may inadvertently penalize groups already marginalized. We implement a fairness-aware aggregation mechanism that monitors for disparities in predictive performance across demographic subgroups (e.g., race, gender, age) and adjusts the aggregation weights to

penalize models that exhibit high subgroup error [19]. This is complementary to local fairness interventions, such as reweighting training samples within each site. Additionally, the explainability module can be used as an auditing tool to detect biased feature associations; for instance, if a model consistently identifies certain zip codes as high-risk without adjusting for structural racism, counterfactual explanations can reveal that the model is effectively discriminating on geography rather than clinical need.

Policy implications extend to regulatory frameworks such as HIPAA in the United States and GDPR in Europe. Federated learning can reduce the legal burden of data sharing by keeping data in place, but it does not eliminate all privacy risks; model inversion attacks may still infer membership or sensitive attributes from parameter updates [20]. Therefore, differential privacy is essential, and we recommend that participating sites conduct a privacy risk assessment before deployment. Furthermore, sustainability requires a governance structure that addresses model updates over time. As clinical practices and SDOH patterns evolve, models must be retrained. We propose a continuous learning protocol where sites periodically contribute new updates, and the central server performs monitoring to detect concept drift. A model registry is maintained to track versioning and audit trails, ensuring that predictions used in clinical decision support are traceable.

6. Deployment and Sustainability

Deploying a federated system in safety-net clinics, community health centers, and public health departments presents practical infrastructure challenges. Many of these organizations operate with limited IT staff, variable internet connectivity, and legacy EHR systems that may not support secure federated communication [21]. Our architecture adopts a lightweight client design: the local training module runs as a containerized service that can be deployed on a standard desktop or server with minimal dependency overhead. Communication between clients and the central server uses asynchronous messaging and can tolerate intermittent connections, with checkpoints to resume training. For sites without sufficient computational resources, we provide a tiered participation mode that allows them to contribute only aggregated statistics or to use a simpler linear model that requires less computation.

Sustainability also depends on long-term funding and institutional commitment. We propose a consortium model where participating sites share the costs of central coordination and receive benefits in the form of a shared model that improves local outcomes. A key performance indicator is the reduction in retention gaps or virologic failure rates as measured by site-level quality improvement metrics. Incentive alignment is critical: sites that contribute high-quality data and diligently update their models should be recognized, while those that free-ride could be restricted from accessing the latest model version. Additionally, the framework must comply with evolving regulatory requirements; embedding automated compliance checks for data use and privacy budgets can reduce administrative overhead.

Robustness to data drift and adversarial attacks is another dimension of sustainability. Adversarial clients could intentionally degrade model performance by sending corrupted updates [22]. We implement anomaly detection on parameter updates using statistical tests to identify outliers, and a reputation system that assigns trust scores to sites based on consistency of their contributions. Similarly, concept drift is monitored by comparing the empirical distribution of predictions at each site against a baseline; if significant drift is detected, the central server can initiate a targeted re-training or recalibration phase.

7. Experimental Design and Evaluation Considerations

While this paper focuses on system architecture rather than empirical results, we outline an evaluation framework that would be used to validate the proposed system. A multi-site simulation using synthetic data derived from public datasets (e.g., NHANES, All of Us public profiles) can be constructed to test the framework under controlled conditions. Key metrics include predictive accuracy (AUROC, AUPRC), calibration (expected calibration error), fairness (disparate impact, equalized odds), privacy (membership inference attack success rate), and communication efficiency (total bytes transmitted, number of rounds to convergence). We compare four configurations: a centralized model that pools all data in one location (unconstrained but most privacy-invasive), a federated model without differential privacy, a federated model with moderate differential privacy (epsilon = 1), and a hybrid approach where sites share only de-identified aggregated SDOH indices while keeping phenotyping private.

Expected results indicate that the federated non-private model approaches centralized performance within one to two percentage points of AUROC, while the differentially private version trades a few points for privacy guarantees. The hybrid model may offer a middle ground for sites that are willing to share low-resolution SDOH summaries. Importantly, the explainability module adds minimal overhead (less than five percent additional training time) and does not degrade predictive performance when explanations are generated offline. Case illustrations can demonstrate how counterfactual explanations reveal actionable interventions: for example, providing transportation vouchers or linking patients to housing services.

8. Discussion and Future Directions

The framework presented here advances the state of the art by integrating federated learning, multimodal SDOH, and explainable AI into a cohesive system for HIV care prediction. The key contribution is not merely a new algorithm but a holistic design that considers the socio-technical constraints of real-world deployment. We acknowledge several limitations. First, the reliance on SDOH data remains challenging because such data are often inconsistently collected or missing, and privacy concerns may prevent sharing even in aggregate. Future work could explore federated transfer learning from non-health sources, such as mobility data or social media, with appropriate ethical safeguards. Second, the fairness-aware aggregation mechanism relies on demographic labels that themselves may be incomplete or biased; algorithmic audits should be complemented by community oversight boards that include people living with HIV. Third, the system assumes a trusted central server; in practice, fully decentralized approaches (e.g., peer-to-peer or blockchain-based) could enhance resilience but at higher communication costs.

Policy implications are far-reaching. Federated multimodal learning could enable a national HIV surveillance and prediction infrastructure without building a centralized database, aligning with recent calls for privacy-preserving public health analytics [23]. However, such an infrastructure requires standardized data models, interoperability across EHR vendors, and funding mechanisms that support sustained operation. The explainability component is especially crucial for regulatory approval: models used to trigger interventions (e.g., case management outreach) must be auditable and contestable. We recommend that future work incorporate human-in-the-loop validation studies, where clinicians and patients interact with the explanations and provide feedback on their utility.

9. Conclusion

Achieving the goal of ending the HIV epidemic demands data-driven tools that are both powerful and respectful of privacy and equity. This paper has presented a federated multimodal learning framework that integrates EHR phenotypes, social determinants of health, and explainable AI to predict HIV care retention and viral suppression. By design, the system addresses the structural trade-offs inherent in distributed health analytics: privacy versus accuracy, interpretability versus complexity, and local autonomy versus global model coherence. We have discussed architecture, governance, deployment, and ethical considerations in depth, emphasizing that technical robustness must be matched by institutional and policy support. The integration of counterfactual explanations and fairness-aware aggregation provides a pathway toward trustworthy AI in HIV care. As federated learning matures and SDOH data become more widely available, such systems can empower clinicians, public health authorities, and communities to intervene earlier and more effectively, ultimately reducing disparities along the care continuum.

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