



Synthesizing Network Science, Graph-Based Deep Learning, and Blockchain in Data Science for HIV Research Addressing Health Inequities and Complex Graph-structured Data

CFAR Symposium on Statistics and Data Science in
HIV Providence Center For AIDS Research

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Outline of this presentation

- Proposed integrated framework: Network science, Graph-structured Data Science Approach, and Blockchain implementation to address HIV Inequities
- Brief Introduction to Social Network Analysis
- Empirical application of social network analysis and graph-based deep learning in HIV research
- Promise of Blockchain implementation to address access to PrEP care continuum for marginalized population

Key Components of the synthesized framework for addressing HIV inequities

- **Social Network Analysis (SNA)**
 - Studying relationships and understanding social structures and dynamics and their impact on social phenomena
- **Graph-based Deep Learning (GBDL)**
 - Learning and extracting features of complex network structures and individual attributes using deep learning techniques
- **Blockchain concept/technology (Blockchain)**
 - The use of cryptography to secure data, decentralized governance, and distributed digital ledger technology to ensure security, transparency, and immutability in the storage, management, and sharing of data among stakeholders.

Proposed integrated framework for graph-structured data science approach and blockchain implementation within network science

- Gain a more complete understanding of health inequities from a network perspective
- Uncover hidden structural patterns
- Make accurate predictions
- Ensure data security and privacy
- Actively engage communities in the research process
- Inform targeted interventions and policy development
- ➡ Creating a more inclusive and equitable health landscape.

Introduction to Social Network Analysis

Network Science and Social Network Analysis

Network Science is defined as the “study of the collection, management, analysis, interpretation, and presentation of relational data.”(p. 3 in Brandes, Robins, McCranie, & Wasserman, in Network Science (2013))

Social Network Analysis provides a common set of methodologies and analytical tools to visualize, measure, and make a statistical inference for various network characteristics (Wasserman & Faust, 1994).

Sources:

Brandes U, Robins G, McCranie A, Wasserman S. What is network science? (2013). *Network science*. 1(1):1-5.

Wasserman S, Faust K. (1994). *Social network analysis: Methods and Applications*.

Utilities of Social Network Analysis

Social network analysis permits us to:

Understand patterns of relationships and network structures

- Visualize patterns
- Describe, measure, and model structural features
- Make statistical inferences about how relations are patterned
 - ➡ Exponential Random Graph Models (ERGMs)

Handling social network data

- Social network data:
 - Recorded by edge list/dyad format or matrix representation
 - Visualized by a graph
 - Structural characteristics are computed by matrix algebra or computer algorithms
 - Network/Sub-network-level: density, network size
 - Node-level: centrality, isolates

Application of Social Network Method to HIV/STI Research



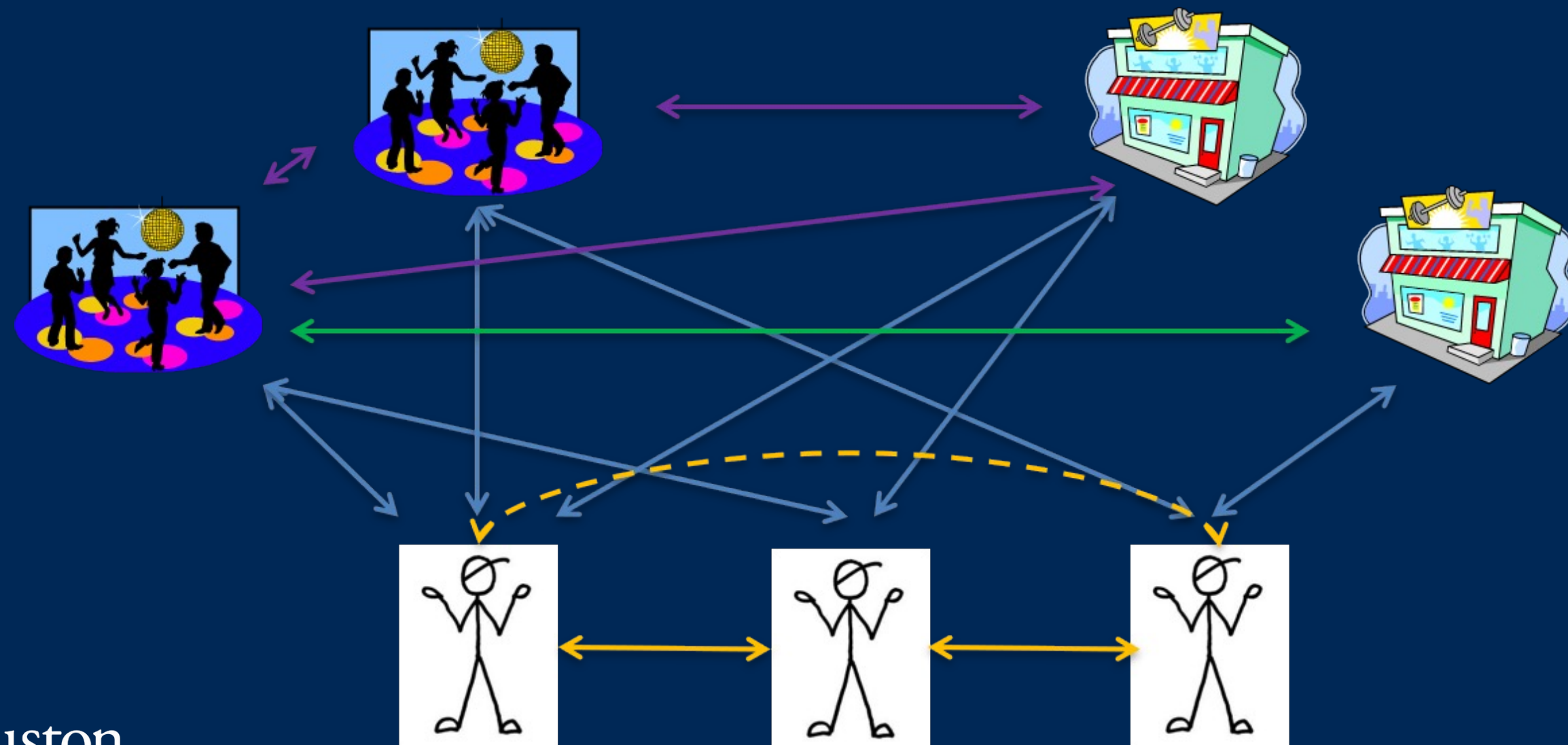
YMAP: Young Men's Affiliation Project of HIV Risk and Prevention Venue

NIH/NIMH 1R01MH100021

(PI: Fujimoto, K. & Schneider, J.A.) 2013-2018

Description of YMAP

Use social network analysis to examine complex multilevel networks among younger sexual minority men aged 16-29 and venue and health organizations in Houston and Chicago



Study design

- At phase I: Sample of venue representative from social& preventive venues
 - 150 venues in Houston & Chicago
 - Wave 1 (2014)
 - Wave 2 (2015)
 - Wave 3 (2016)
- At phase II: RDS Sample (Network-based link-tracing chain referral recruitment method) of 755 sexual minority men in Houston & Chicago
 - Wave 1 (2014-15)
 - Wave 2 (2015-16)

→ The retention rate was 79%



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Statistical adjustment of network degree in respondent-driven sampling estimators: Venue attendance as a proxy for network size among young MSM

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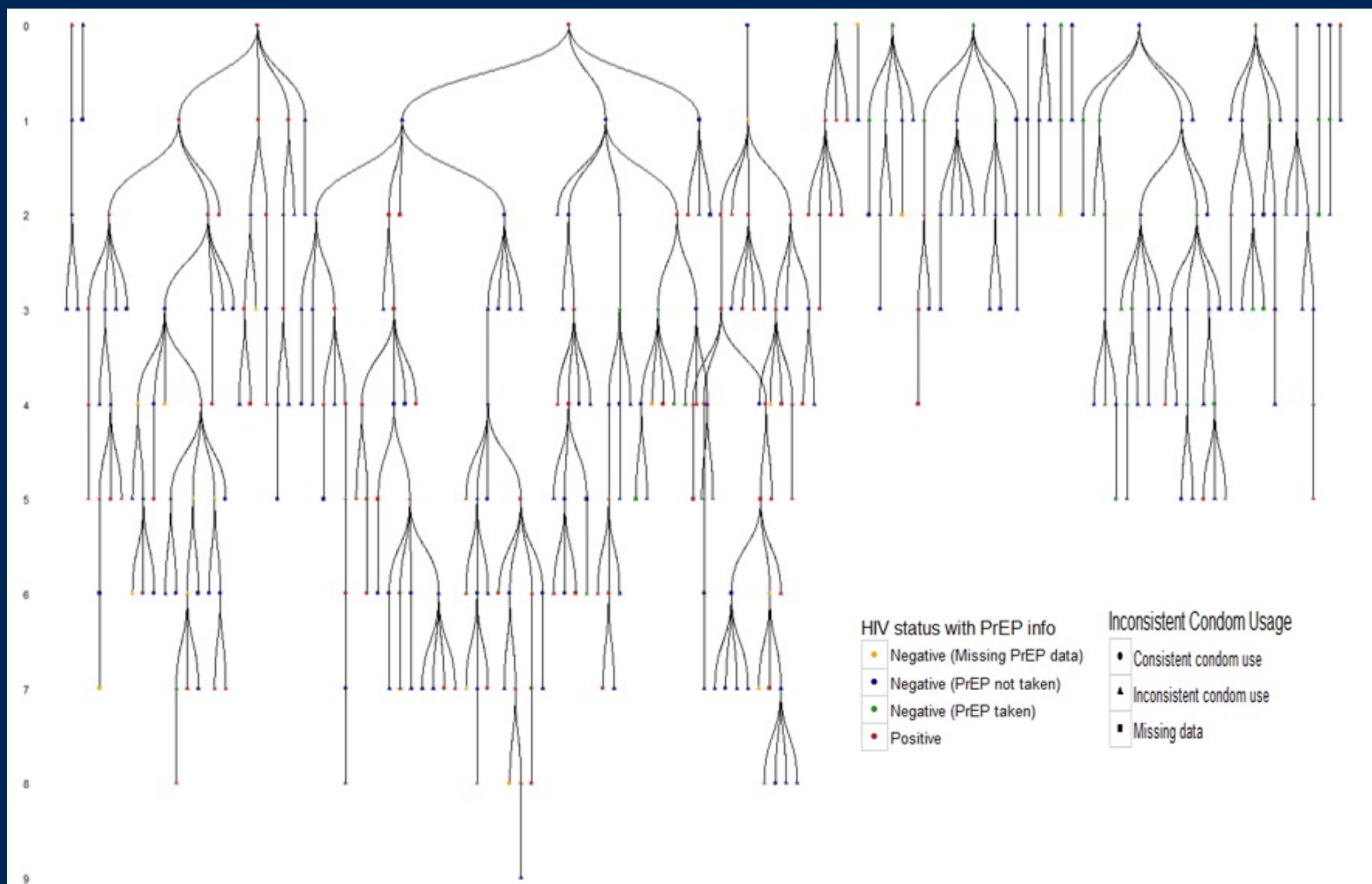
ABSTRACT

We introduce a new venue-informed network degree measure, which we applied to respondent-driven sampling (RDS) estimators. Using data collected from 746 young MSM in 2014–2016 in Chicago, IL, and Houston, TX, we estimated the population seroprevalence of HIV and syphilis and risk/protective behaviors, using RDS estimates with self-reported network size as a standard degree measure as well as our proposed venue-informed degree measure. The results indicate that the venue-informed degree measure tended to be more efficient (smaller variance) and less biased than the other measure in both cities sampled. Venue attendance-adjusted network size may provide a more reliable and accurate degree measure for RDS estimates of the outcomes of interest.

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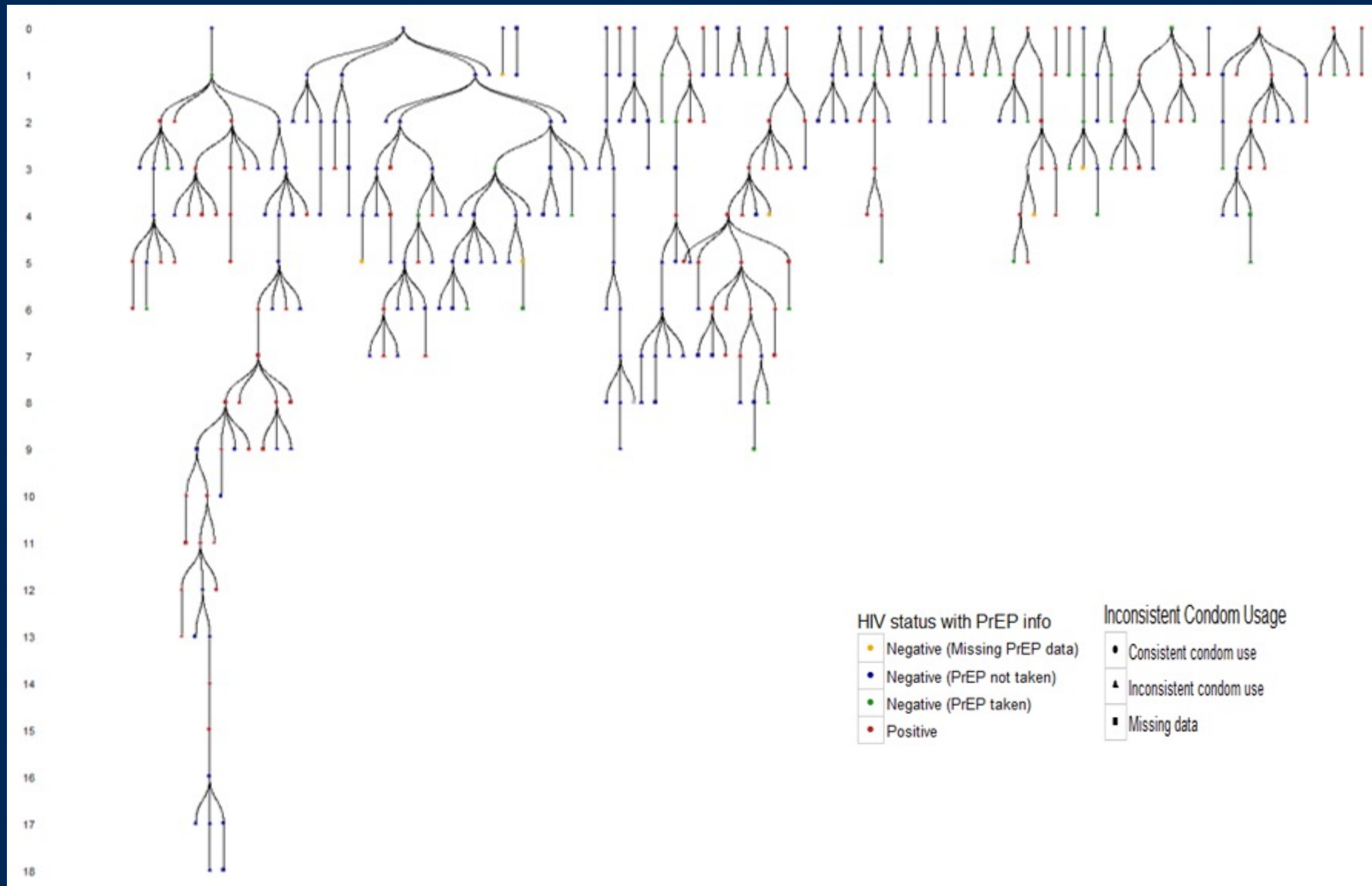
RDS Chains among YMSM for Chicago, excluding non-sprouted seeds

(The longest recruitment chain per site was 9 waves, with 34 seeds (constituting 9.0% of the sample) recruited)



RDS Chains among YMSM for Houston, excluding non-sprouted seeds

(The longest recruitment chain per site was 18 waves, with 63 seeds (constituting 16.7% of the sample) recruited)



Statistical network model: Exponential Random Graph Modeling (ERGM)

- Statistical method of directly modeling **observed network**
- Test whether there are statistically significant structural characteristics in the **observed network**
 - Assess if these **characteristics** are more likely to be observed in the network than randomly generated networks

Formulation: ERGMs

ERGMs take the form of probability distribution of graph
(for all tie-variables simultaneously)

$$P(Y=y)=1/(k(\theta)) \exp\{\theta^{\wedge'} g(y)\}$$

Y is a set of tie indicator variables Y

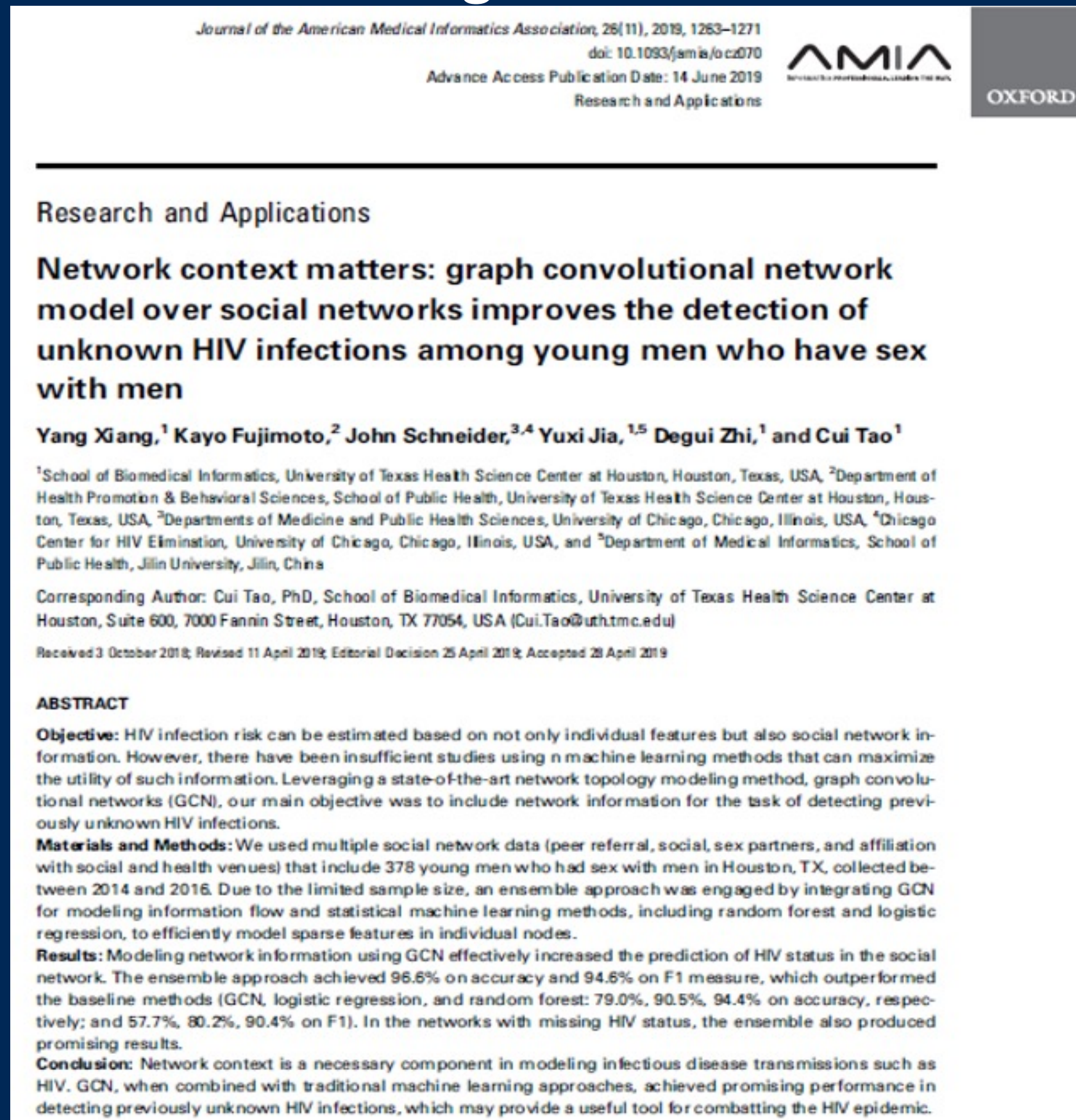
y is a realization, the observed network

$g(y)$ is a vector of network statistics

θ is a parameter vector corresponding to $g(y)$

$k(\theta)$ is a normalizing factor calculated by summing up
 $\exp \{\theta^{\wedge'} g(y)\}$ over all possible network configurations

Empirical application of GCN using YMAP data



Source: Xiang, Y., Fujimoto, K., Schneider, J. A., Jia, Y., Zhi, D., & Tao, C. (2019). Network context matters: Graph convolutional network model over social networks improves the detection of unknown HIV infections among young men who have sex with men. *Journal of the American Medical Informatics Association (JAMIA)*, 26(11), 1263–1271.

Overview of ensemble approach GCN for modeling information flow and statistical machine learning methods (random forest and logistic regression)

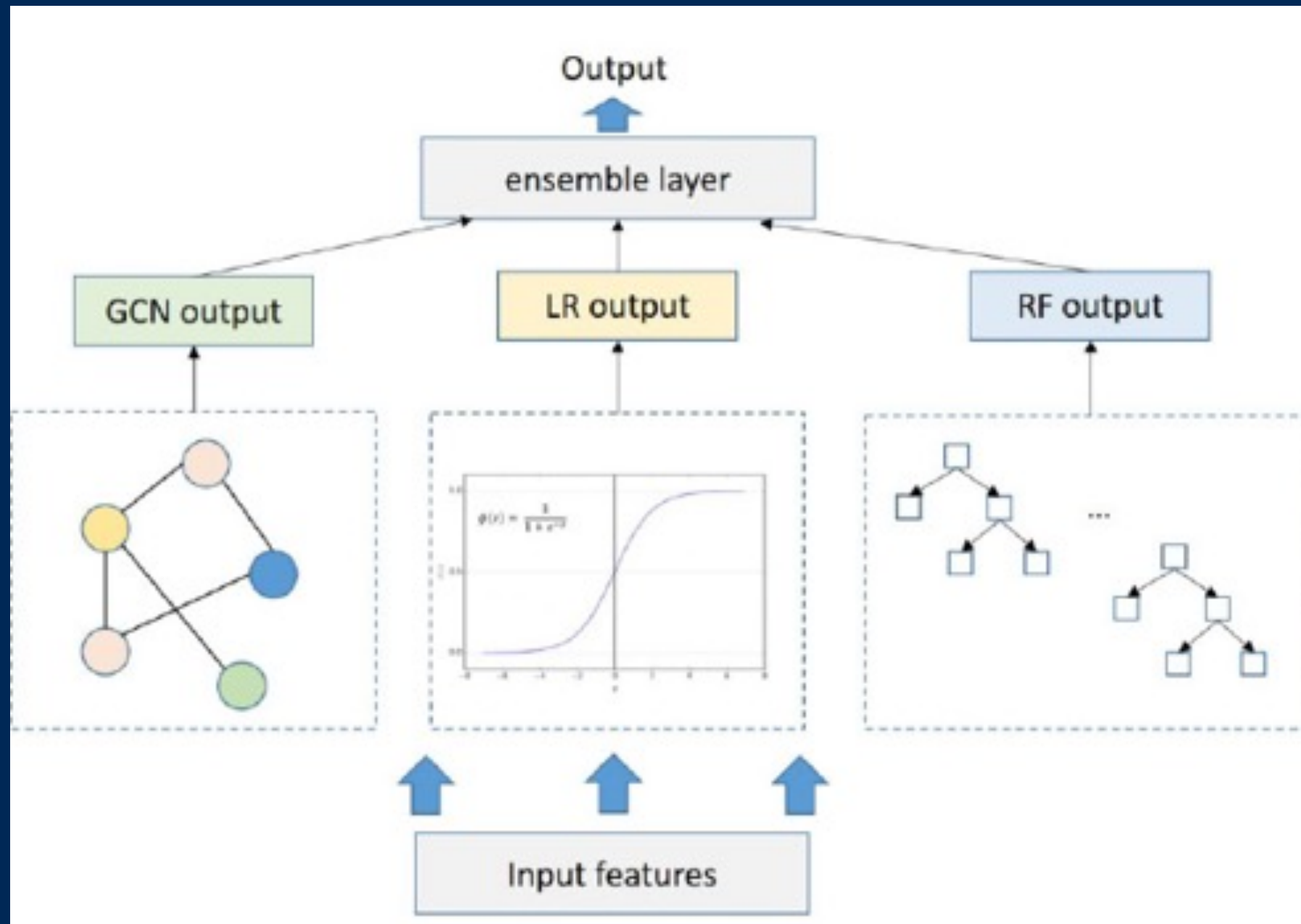


Table 2. Prediction performance for different classifiers in percent (standard deviation of 10 rounds of resampling)

Method	Accuracy(%)	F1(%)
GCN	79.0(± 2.72)	57.7(± 6.83)
LR	90.5(± 2.69)	80.2(± 7.48)
RF	94.4(± 2.76)	90.4(± 4.38)
GCN+LR	93.4(± 3.09)	88.4(± 5.30)
GCN+RF	96.6(± 1.97)	94.6(± 2.88)
LR+RF	95.3(± 2.75)	91.6(± 5.64)
GCN+LR+RF	96.5 (± 2.05)	94.5(± 3.12)

GCN effectively increased the prediction of HIV status in the social Network, achieved 96.6% on accuracy and 94.6% on F1 measure, which outperformed the baseline methods

Empirical application of GAT using YMAP data

Identifying influential neighbors in social networks and venue affiliations among young MSM: a data science approach to predict HIV infection

Yang Xiang^a, Kayo Fujimoto^b, Fang Li^a, Qing Wang^a,
Natascha Del Vecchio^c, John Schneider^{c,d}, Degui Zhi^a and Cui Tao^a

Objective: Young MSM (YMSM) bear a disproportionate burden of HIV infection in the United States and their risks of acquiring HIV may be shaped by complex multilayer social networks. These networks are formed through not only direct contact with social/sex partners but also indirect anonymous contacts encountered when attending social venues. We introduced a new application of a state-of-the-art graph-based deep learning method to predict HIV infection that can identify influential neighbors within these multiple network contexts.

Design and methods: We used empirical network data among YMSM aged 16–29 years old collected from Houston and Chicago in the United States between 2014 and 2016. A computational framework GAT-HIV (Graph Attention Networks for HIV) was proposed to predict HIV infections by identifying influential neighbors within social networks. These networks were formed by multiple relations constituted of social/sex partners and shared venue attendances, and using individual-level variables. Further, GAT-HIV was extended to combine multiple social networks using multigraph GAT methods. A visualization tool was also developed to highlight influential network members for each individual within the multiple social networks.

Results: The multigraph GAT-HIV models obtained average AUC values of 0.776 and 0.824 for Chicago and Houston, respectively, performing better than empirical predictive models (e.g. AUCs of random forest: 0.758 and 0.798). GAT-HIV on single networks also delivered promising prediction performances.

Conclusion: The proposed methods provide a comprehensive and interpretable framework for graph-based modeling that may inform effective HIV prevention intervention strategies among populations most vulnerable to HIV.

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AIDS 2021, **35** (Suppl 1):S65–S73

Source: Xiang, Y., Fujimoto, K., Li, F., Wang, Q., *Del Vecchio, N., Schneider, J. A., Zhi, D., & Tao, C.

(2021). Identifying influential neighbors in social networks and venue affiliations among young MSM: A data science approach to predict HIV infection. *AIDS*, 35(Suppl 1), S65–S73.

Empirical application of organizational network in PrEP care delivery system using YMAP



[Networks, Knowledge Brokers, and the Public Policymaking Process](#) pp 265–314 | [Cite as](#)

Brokerage-Centrality Conjugates for Multi-Level Organizational Field Networks: Toward a Blockchain Implementation to Enhance Coordination of Healthcare Delivery

[Kayo Fujimoto](#) , [Camden J. Hallmark](#), [Rebecca L. Mauldin](#), [Jacky Kuo](#), [Connor Smith](#), [Natascha Del Vecchio](#), [Lisa M. Kuhns](#), [John A. Schneider](#) & [Peng Wang](#)

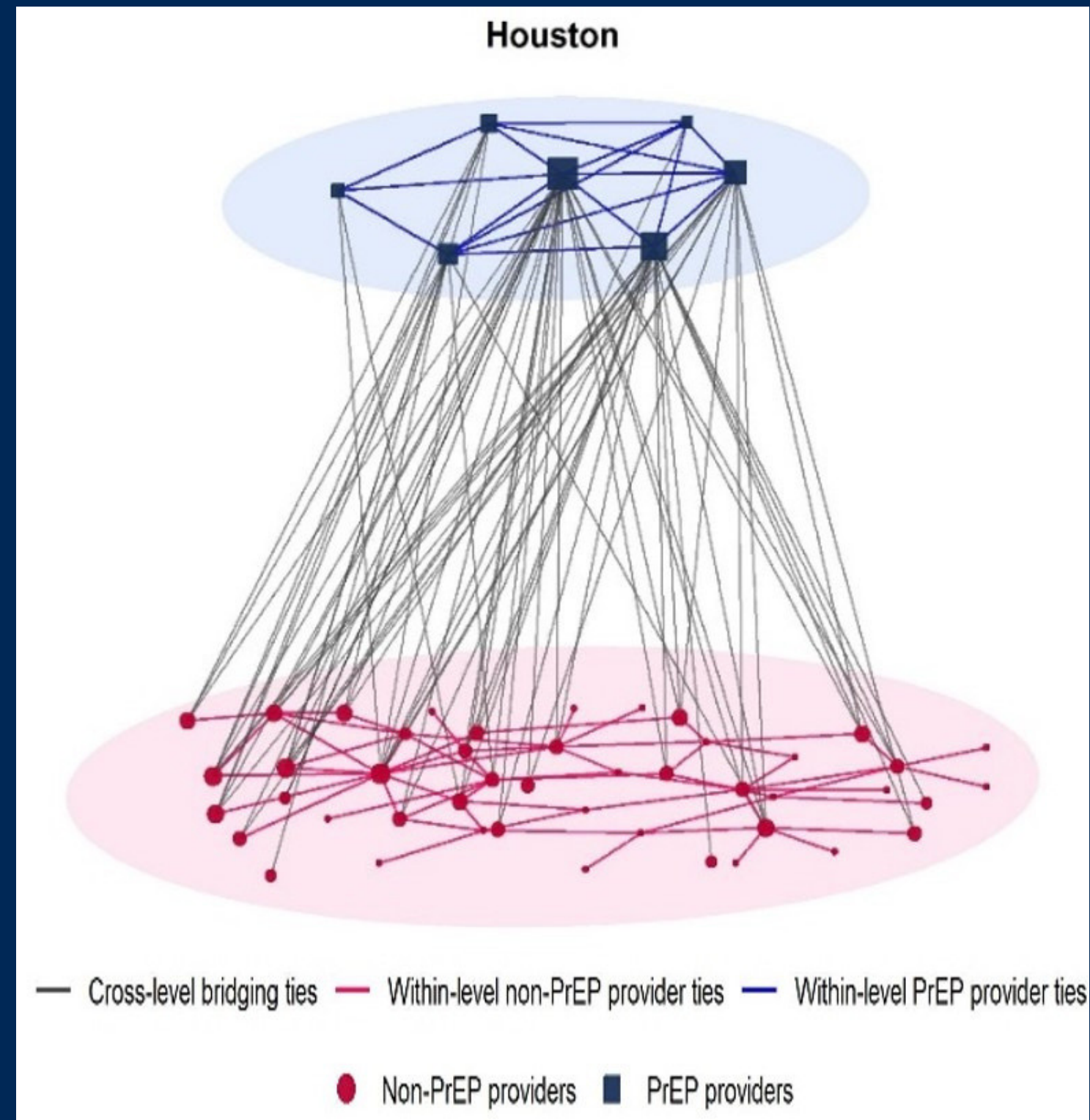
Chapter | [First Online: 04 November 2021](#)

220 Accesses

Abstract

A fragmented U.S. healthcare delivery system may reflect a highly brokered communication network controlled by only a few brokers. Such relational inequality in brokerage influences the formation of interorganizational brokerage relations. This chapter presents the theoretical mechanisms that underlie the reasoning of instantiating organizational power dynamics in controlling communication (brokerage) while increasing connectivity (degree centrality); determining opportunities for accessing and exchanging resources across subgroups; and shaping organizational decisions and actions that are transformed collectively into locally centralized or decentralized brokerage structures, called ‘brokerage-centrality conjugates.’ These conjugates make up the interorganizational collaboration network of an organizational field, and is tested and supported by multi-level exponential random graph models. Finally, a blockchain-based network intervention is proposed to enhance interorganizational communication and coordination to improve population health.

Multilevel collaboration network in PrEP care delivery system



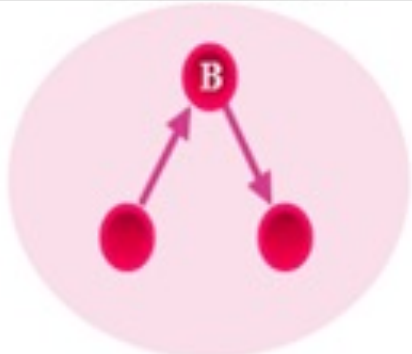
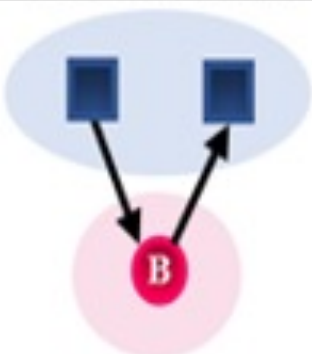
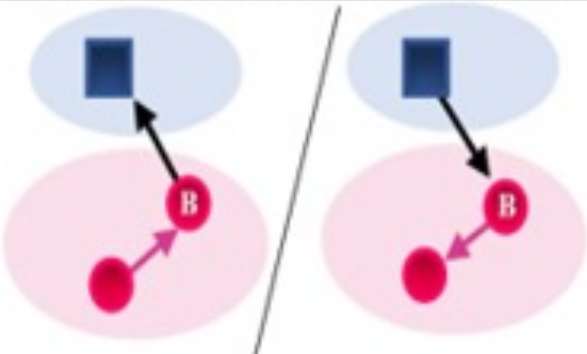


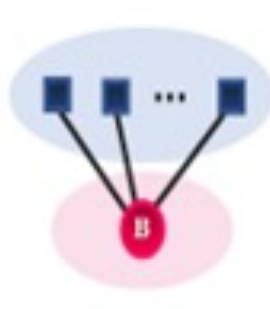
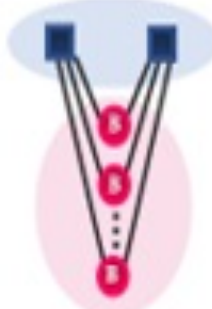
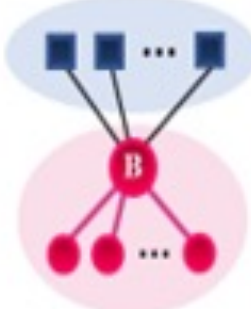
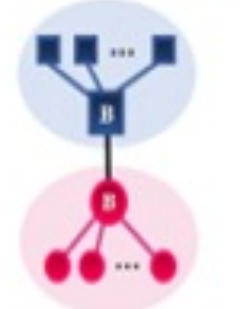
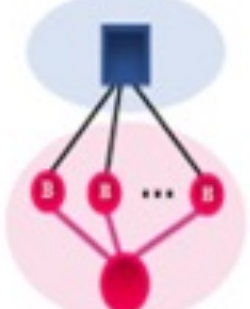
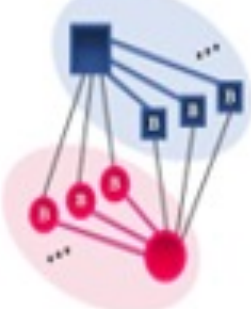
Source: Fujimoto, K., Hallmark, C. J., Mauldin, R. L., Kuo, J. C., Smith, C., Del Vecchio, N., Kuhns, L. M., Schneider, J. A., & Wang, P. (In Press). Brokerage-centrality conjugates for multi-level organizational field networks: Toward a blockchain implementation to enhance coordination of healthcare delivery. (Eds.) Weber, M. S., & Yanovitzky, I. Networks, Knowledge Brokers, and the Public Policymaking. Springer International Publishing AG, Cham.

Local structural configurations (motifs)

Brokerage structures by Gould & Fernandez (1989)

and our extension

Typology of Brokerage-Centrality Conjugates: Non-PrEP Providers as Brokers



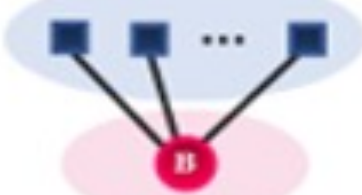

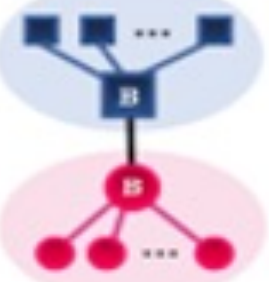
Type of brokerage role	Coordinator		Cosmopolitan		Representative/Gatekeeper			
Gould and Fernandez's typology of brokerage role								
Proposed typology of brokerage-centrality conjugate role								

Letter B in the circles or squares represent broker organizations(s).

These were all significant positive estimates, indicating that these structural configurations are more likely to be observed in the network than randomly generated networks.

Results of important structural configurations that drive collaboration network in PrEP delivery system

We observe some bottleneck structures with a single broker or multiple brokers connected through the same pair of organizations.

Configurations	Houston	
	Parameter	SE
	1.084	0.373
	0.096	0.015
	1.492	0.411
	0.121	0.012
	0.095	0.014

Implementation challenges in local PrEP care delivery system in Houston

- **At the individual level:** PrEP uptake among most-at-risk younger MSM of color is low
 - Social determinants of health such as unemployment, housing instability, incarceration, stigma, discrimination.
- medical mistrust and distrust.
- **At the organizational level:** The existing client referral system generate bottleneck and concentration of information and resources in the local PrEP referral network
 - PrEP referrals are made based on existing relationships with specific providers (i.e., within-organizational referral), or a few prominent providers or health agencies
 - ➔ generate hubs of information and resource flows, being incapable of handling sudden environmental changes (e.g., the COVID- 19 pandemic)
 - **At the community level:** The existing client referral system may drive fragmented local PrEP care delivery system.

Technological solution for PrEP implementation challenge: “Blockchain-based network intervention”

What is **Blockchain**?

- Distributed ledger technology,
- Highly secured, decentralized database system that is maintained by every participant in a peer-to-peer (P2P) network **without central authority as an intermediary**.
- Decentralized governance (consensus algorithms) and shared ownership.

Blockchain Project Aims/Objectives

- **Aim 1:**
 - To develop a schema to capture the data elements that will be required to report HIV status information
 - Time, date, type, location, result, of the HIV test).
- **Aim 2:**
 - To identify antecedent and anticipated implementation outcomes:
 - Acceptability, feasibility, adoptability, implementability
 - Potential determinants of implementing TestLinker among community stakeholders

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Thanks for your attention

Any ideas?

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