

## **Breakout Session 4: Track B**

# **Alcohol Use Disorder (AUD) Treatment Simulation**

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# Alcohol Use Disorder (AUD) Treatment Simulation

**Using Cloud Computing to Model Treatment Impacts on Alcohol-Related Disparities**  
(R01AA029812-02-S1)

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# General Background

- Marked disparities are found for alcohol use, alcohol-related problems, and utilization of alcohol health services across racial & ethnic, socioeconomic, gender, and urban/rural subgroups in the US
- Goal of this project is to identify strategies that would reduce disparities in alcohol use disorder (AUD) and alcohol health services access
  - Universal implementation of evidence-based practices (EBPs) such as
    - Screening
    - Brief intervention
    - Referral to treatment
    - Medication-assisted treatment/pharmacotherapy
  - Increasing treatment capacity in existing programs
  - Adding treatment programs in underserved areas



# Aims of Main Study



**Aim 1:** Determine whether (a) implementing evidence-based practices (EBPs) universally in primary care for screening, brief intervention, and referral to treatment and in specialty AUD treatment for pharmacotherapy and (b) extending these EBPs to underutilized, nontraditional settings would reduce or exacerbate AUD treatment disparities.



**Aim 2:** Evaluate whether (a) improving geographic accessibility and availability to specialty care and community-based mutual help (such as Alcoholics Anonymous); (b) improving affordability; and (c) increasing acceptability (particularly Spanish-language services) would reduce or exacerbate AUD treatment disparities.



**Aim 3:** Estimate cost and cost-effectiveness of the key interventions in Aims 1 and 2 and compare them with the status quo and with each other.

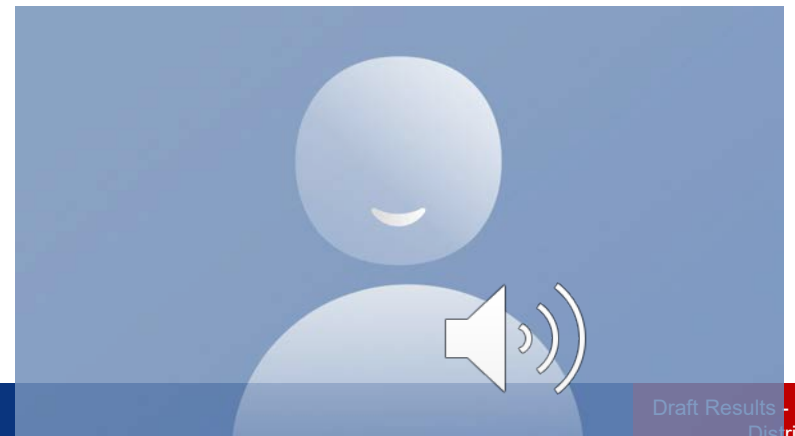


# General Model Background

- We are building (in Python) and calibrating a spatial microsimulation model of alcohol health services for people with mild, moderate and severe AUD
  - Model implements the notion of geographic space but does not model space explicitly
    - model does not have an underlying topology like a grid; individuals don't move in space
    - model has implied space through assigned lat/lon coordinates and distance preferences
- We model differential access to care, including both treatment entry and completion
- We will make long-term projections (over 10 to 20 years) for AUD severity and recovery status for key population subgroups over time
- We model the populations of California and Texas (chosen to best simulate disparity impacts)
  - Demographically and geographically diverse states



# Why do we need the cloud?

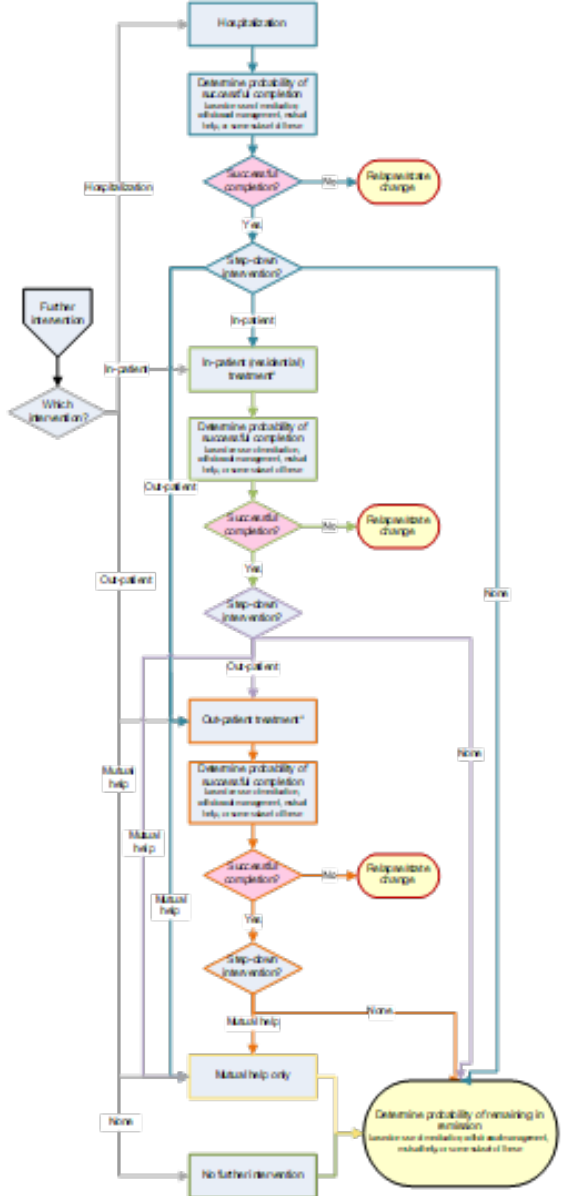
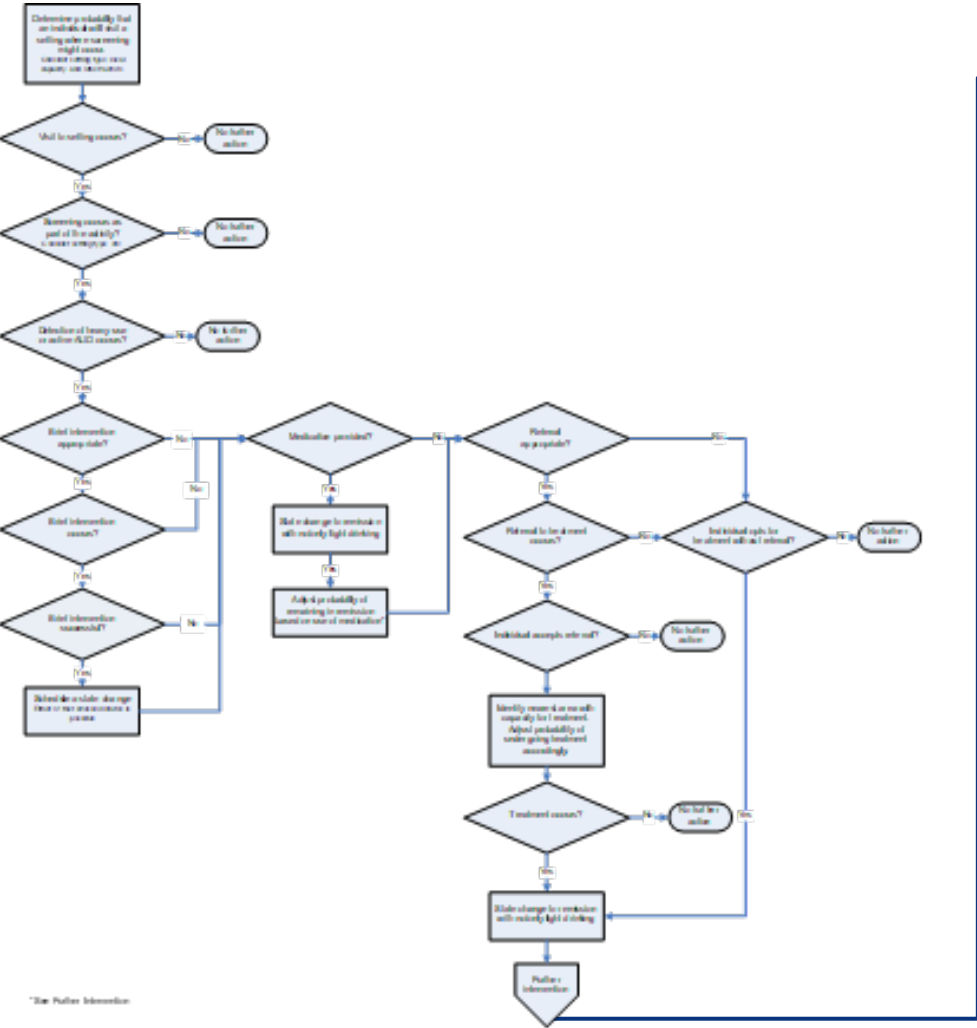


# Why do we need the cloud?

- Model is complex
  - Many decision points where individual trajectories diverge
- Populations are large
  - California: ~ 39 million individuals
  - Texas: ~ 30 million individuals
- Local microsimulation instance has computational limits (even on a Mac m1/2/3)
  - Can only run with sub-populations (especially in urban areas) to reduce number of simulated individuals
  - Imposes artificial geographic boundaries
- Space matters, but geographic boundaries should not
  - Nearest treatment facility with availability might be in a different county or state
- Scalable cloud setup provides performance benefits

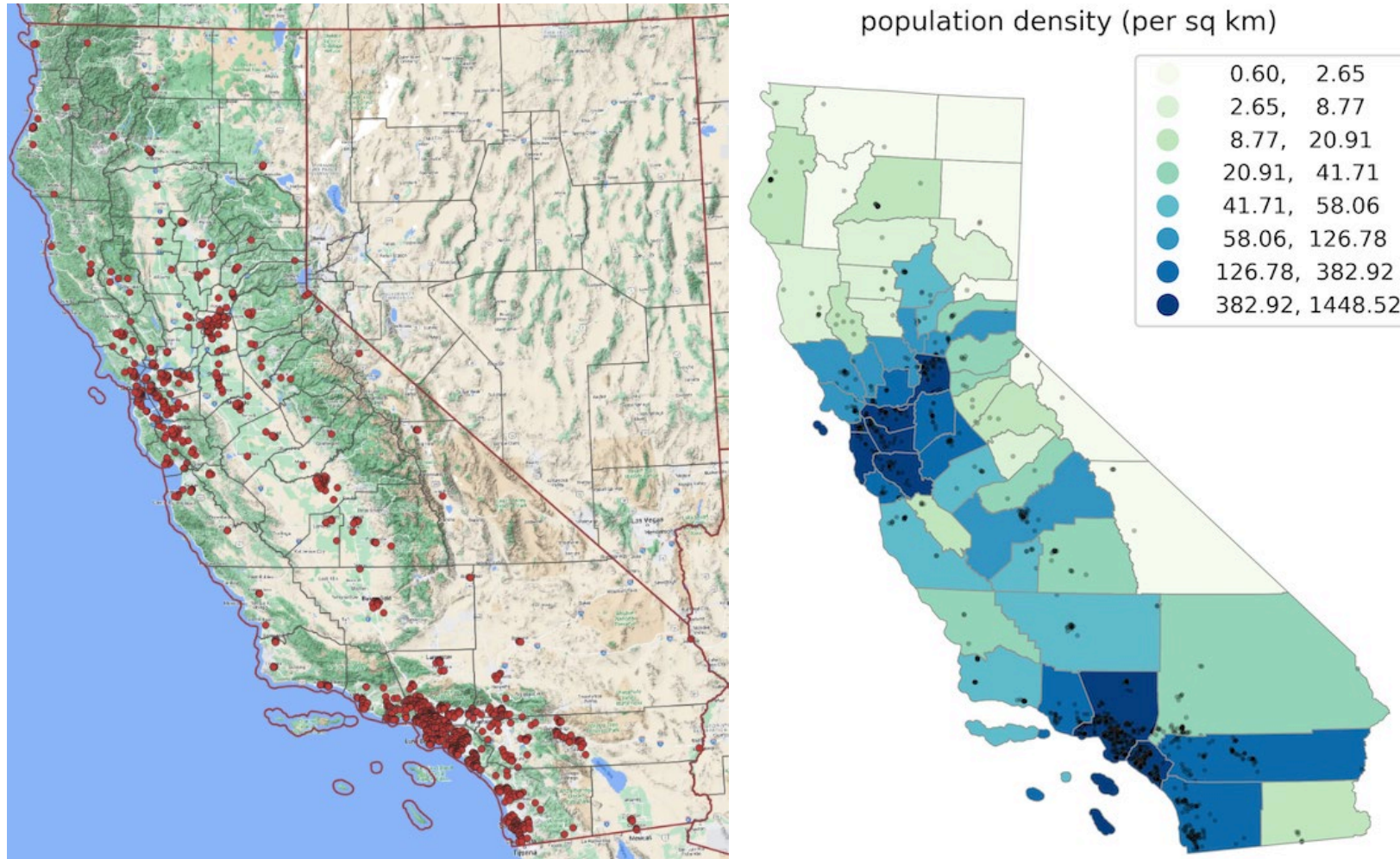


# Problem: Highly-Complex Simulation Model





# Problem: Large Populations & Varied Geographies of CA & TX



Left: Locations of substance use treatment facilities in CA (retrieved from SAMHSA treatment locator at <https://findtreatment.gov/locator> )

Right: Treatment locations relative to population density per square mile



# Cloud-Based Distributed Computing – MPI (Message Passing Interface)

- In cloud-based model
  - All counties in state are modeled simultaneously, with agents permitted to engage with any alcohol-related health services, not just with those in their immediate vicinity
    - Removes artificial geographic borders constraint
    - This is essential, as patients do not engage with alcohol health services exclusively in proximity to their home
    - Further, some counties are essentially treatment deserts without adequate treatment infrastructure, which necessitates cross-county health services access
- Options to parallelize the model in the cloud
  - Use Python multiprocessing module
  - Run many instances of the model in parallel with different sub-groups
    - Artificial boundaries constraint
  - Use MPI based solution written in Python (repast4py)
    - Based on the well established C++ Repast Simphony HPC package
    - <https://repast.github.io/repast4py.site/index.html>



# MPI Solution - Advantages

- Distributed out of the box
  - We can focus on the model, not on underlying compute infrastructure
- Different compute nodes can communicate with each other
  - We use this to implement a single treatment facility manager (responsible for all facilities) that every individual has access to
    - Irrespective of the compute node a particular individual is allocated to
- In the example on the right, P1 and P2 are different compute nodes and A1 and B2 are different individuals
  - A1 and B2 can interact through so-called ghost agents (represented by circles with dashed lines)

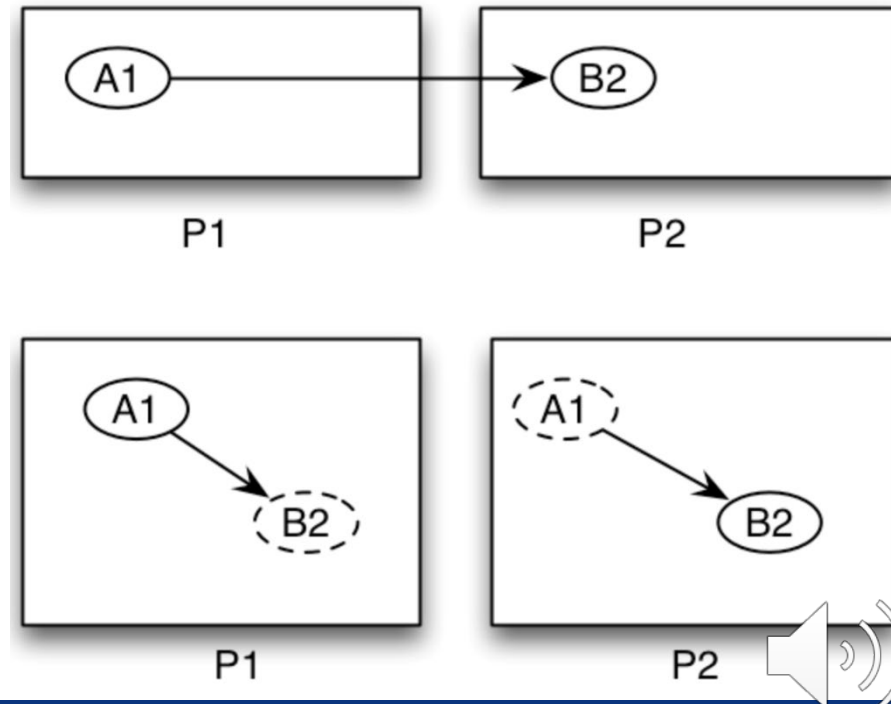


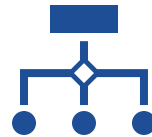
Image source: repast4py user guide

# Applying MPI-Based Cloud Computing Infrastructure



## Build

**Aim 1:** Build proof-of-concept examples and evaluate cloud service options capable of providing scalable cluster computing for Message Passing Interface (MPI)-based simulation modeling software.



## Compare

**Aim 2:** Compare simulation results for a computationally constrained laptop-run model with results from running same model on a scalable cloud computing cluster.



## Evaluate

**Aim 3:** Evaluate costs for setting up and running simulation model (including data ingress, run time, and data egress) for execution on cloud solution compared to running model on high-performance laptop.



# Progress to Date

- Installed *repast4py* MPI simulation package in two different cloud environments (Amazon AWS and Microsoft Azure)
- Successfully executed example simulations provided by *repast4py*
  - One example simulation is very simple zombie simulation
  - Underlying topology is a grid where both zombies and humans randomly move across cells
  - Ran zombie simulation in both cloud environments with 50 million agents to demonstrate validity of MPI approach



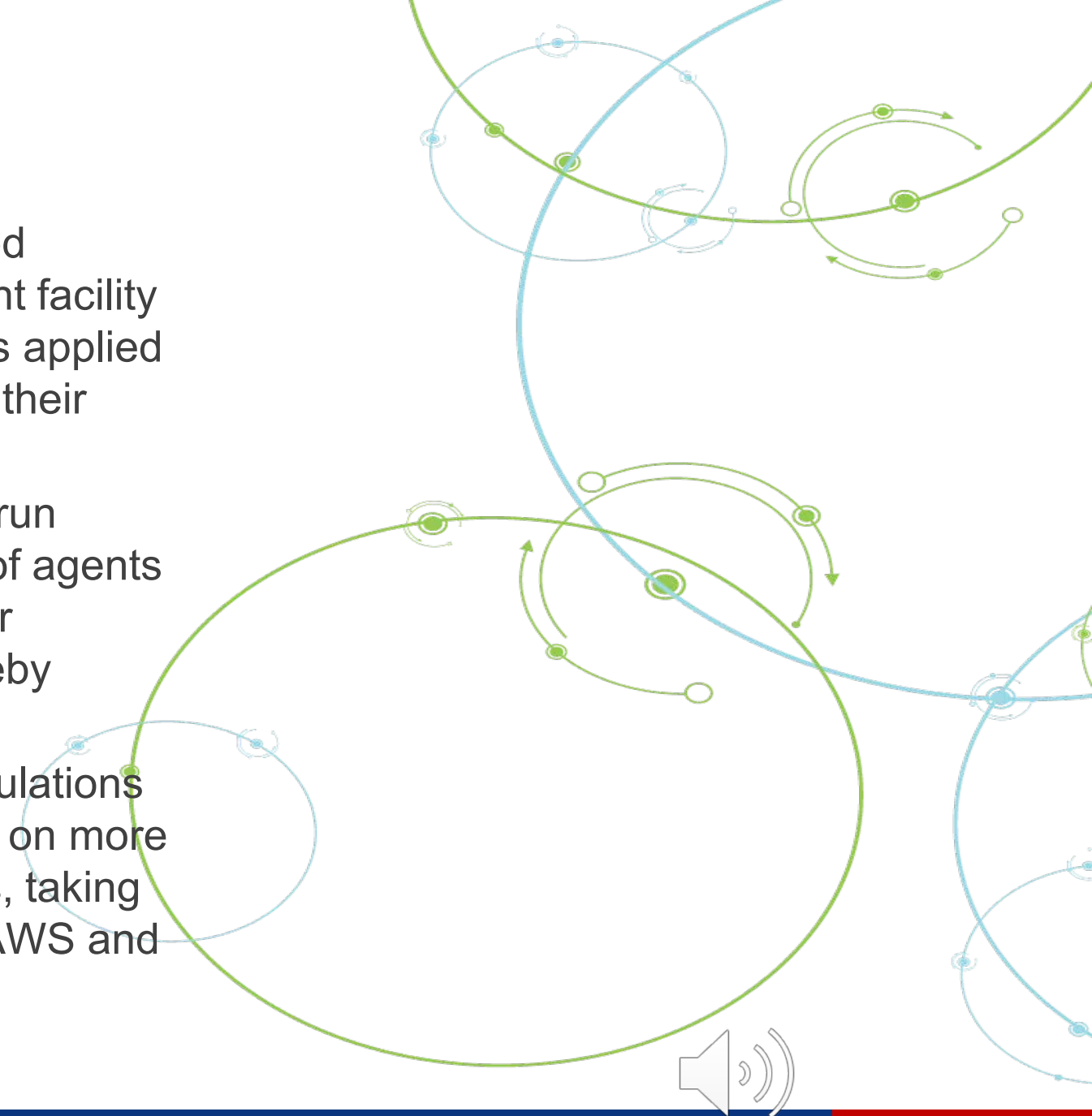
# Progress to Date

- Implemented simple version of non-MPI AUD treatment model using *repast4py*
- Focused on individuals with AUD seeking treatment at one of  $n$  available treatment facilities
- Individuals and facilities assigned specific locations (latitude/longitude coordinates) and individuals also express preference for a certain treatment facility based on proximity
- Each facility has limited number of treatment slots available
  - Scheduling challenge where individuals apply for treatment and need to await their turn in the case where all treatment slots are occupied



# Initial Results

- Able to run spatially unconstrained simulations with a single treatment facility manager agent, where individuals applied for treatment slots irrespective of their latitude/longitude
- Preliminary results show we can run simulations with a large number of agents that correctly get assigned to their requested treatment facility, thereby satisfying scheduling constraints
- Will test full model with large populations (more than 10 million individuals) on more powerful hardware configurations, taking advantage of easy scalability of AWS and Azure cloud environments





## **Additional Team Acknowledgements:**

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# **Thank you**

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