Agent-based Models

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Outline

- Definitions
- Key properties
- Interaction/Network
- Main uses
- Assumptions
- Strengths and limitations
- Examples and impact

Definition and History

Agent-based Models—What is it?

- Agent-based models (ABMs) are a class of computational models that involve agents, often representing individuals, to interact producing results in an entire system of interest
- Agents represent individuals with heterogeneity in their characteristics
- Agents comprise and impact a larger system, such as a certain population defined by geography, a healthcare system, or health status

Marshall et al. 2015, 2017; Rothman, 2021.

ABMs—How do they work?

- Include parameters, parametric models, or algorithms to describe how agents interact, which can be deterministic or stochastic functions.
- Once the features set, model repeatedly run (i.e., model runs) and outcomes assessed at specific time points in the model, averaging over the model runs to obtain results.

El-Sayed & Galea, Systems Science and Population Health. Oxford; New York: Oxford University Press, 2016

ABMs—History

- Assess interventions and policies in a population or geographic area by assessing the impact on disease prevalence and incidence.
- Used extensively to improve understanding of HIV prevention and treatment and improve the prevention of opioid overdoses and treatment of opioid use disorder.

Marshall, B. D., & Galea, S. *AJE*, 2015; Tracy, M. et al. *Ann Rev Public Health*, 2018; Mattie, H., et al. *JAIDS*, 2022.

Key Properties

Target Population Setting

- Specific population, defined by types of individuals, geography, and time.
- This specification can help focus the information needed to parameterize the model, and also for calibration (fit known data) and validation (predict/generalize in new data).

Aggregate vs. individual

- ABMs are individual simulation models
- Simulated individuals -agents
- Individual units are referred to as agents and typically represent individuals, such as patients, study participants, or members of a specific population
- Agents can also be entities like schools, hospitals, providers

Individual Characteristics

- Defined for each agent or group of agents, such as sociodemographic, clinical factors, and disease status
- Defined by single parameters or parameters following specific distributions.

Behavior characteristics

- Agents are assigned behavior related to the exposure process, disease process, and interactions with other agents.
- Example:
  - Agents could be assigned a certain probability of adherence to medication for opioid use disorder conditional on their baseline characteristics, such as how long they have been using opioids.
  - Agents with certain characteristics such as substance use to be more likely to partner with each other, compared to those who do not share this behavior.

Time

- Agent-based models are typically rerun at discrete time steps, such as a day or month
- Outcomes are assessed after a pre-defined meaningful time interval.
- Outcomes are typically assessed for groups of agents at specific time points, defined by the research question of interest.

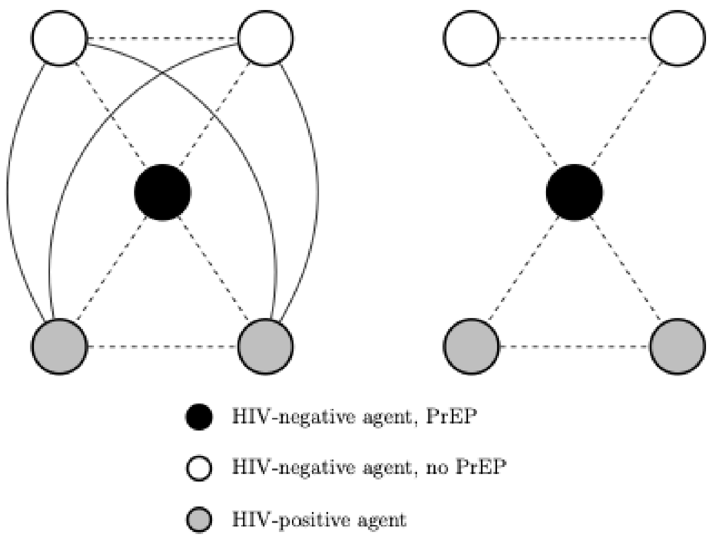
Modeling Workflow

- ABMs are developed and parameters specified
- Calibrated and validated in specific research settings.
- Uncertainty is captured through simulation intervals, which are calculated using percentiles of the outcome distribution across the simulation runs

Network and Interaction

Interaction/Network (1)

- Agents interact with each other in a simulated setting, which can impact their own behavior and the interaction itself.
- Interaction often based on network interaction
- Networks can be defined using a bottom-up or top-down approach.



Interaction/Network (3)

- Botton up:
  - Agents are assigned rules for partnering with other agents that can be either deterministic or stochastic rules.
  - Once these rules are assigned, agents then form partnerships that can either remain stable for the duration of the follow-up in the model, or dissolve at the end of the time step, then new relationships are possibly reformed.

Interaction/Network (3)

- Top down:
  - A network model is imposed on the agents, such as preferential selection or random mixing, then the connections observed under this network model are used to define the partnerships between in the network.
  - For example, the network could be simulated using an exponential random graph model (ERGM) based on features such as partnerships and partnership duration from network studies in the target population of interest.

Robins, G., et al. *Social networks, 2017*.

Interaction/Network (4)

- Temporal ERGMs can be used to simulate networks that change over time in the ABM.
- Recent developments in exponential random graph (p*) models for social networks. Soc Networks 2007; 29:192–215.
- ABMs with networks:
  - TITAN Model: https://www.titanmodel.org
  - EpiModel: https://www.epimodel.org/

Main Uses

ABMs - Main Uses (1)

- Evaluate the impact of interventions and policy by manipulating the individual-agent characteristics.
- Pre-deployment evaluation of interventions in simulated populations.
- Ideal for evaluating intervention strategies prior to implementation in real-world settings
- Streamline the intervention development process and identify effects not be readily apparent from empirical studies

ABMs - Main Uses (2)

- ABMs are a useful to simulate randomized trials and other designs when real-world studies are not ethical or feasible.
- Novel approaches to understand the conditions under which the results from ABMs confer causal interpretations are needed (Buchanan et al. 2021, 2023, Murray et al. 2019, Marshall et al. 2015).

Assumptions

Assumptions (1)

- **Heterogeneity of Agents:** Agents can differ in attributes (e.g., age, risk behavior, network connections) and decision rules.
- **Rule-Based Behavior:** Agent actions are governed by predefined rules, which may include probabilistic or deterministic decision-making.
- **Local Interactions:** Agents interact with others based on a defined network or spatial proximity (e.g., contact networks or neighborhoods).
- **Autonomy and Adaptation:** Agents act independently and can adapt behavior over time based on experience or environment.

Assumptions (2)

- **Stochasticity:** Randomness is often introduced in agent attributes, behaviors, and interactions to capture real-world variability.
- **Environment Specification:** The simulated environment (social, spatial, institutional) must be defined and may influence agent behavior and outcomes.
- **Initial Conditions and Parameters:** The model outcome is sensitive to initial states and parameter choices—requiring calibration and validation with real data.

Strengths and Limitations

Strengths and Limitations (1)

- Rely on many parameters and their corresponding distributional assumption that are typically ascertained from the published literature and real-world studies.
- If parameters not be known (or known with substantial uncertainty), sensitivity analyses can be performed by searching across a grid of possible parameter values and assessing the impact on model outcomes.

Strengths and Limitations (2)

- ABMs are likely underestimating uncertainty in the model because parameters either known or unknown uncertainty included
  - Parameters may be treated as fixed values (a certain percentage increase in disease risk)
  - Parameters follow a distribution (mean number of sexual acts following a Poisson distribution with a certain rate parameter)
  - Simulation intervals: Nonparametric way to capture this uncertainty to an extent
  - If the model assumes a value is known, the uncertainty is likely underestimated.

Strengths and Limitations (3)

- Recent work developed the conditions under which ABM results could be causally interpreted
  - Using a trial emulation approach, ABMs can be used to simulate randomized trials and then use causal inference methods to identify and estimate causal effects.
  - Alternatively, the ABM can be run under the treatment and control conditions separately, and the outcomes of these two models can be compared.
- Careful consideration is needed when using network ABMs to ensure we are validly identifying and estimating causal effects.

Strengths and Limitations (4)

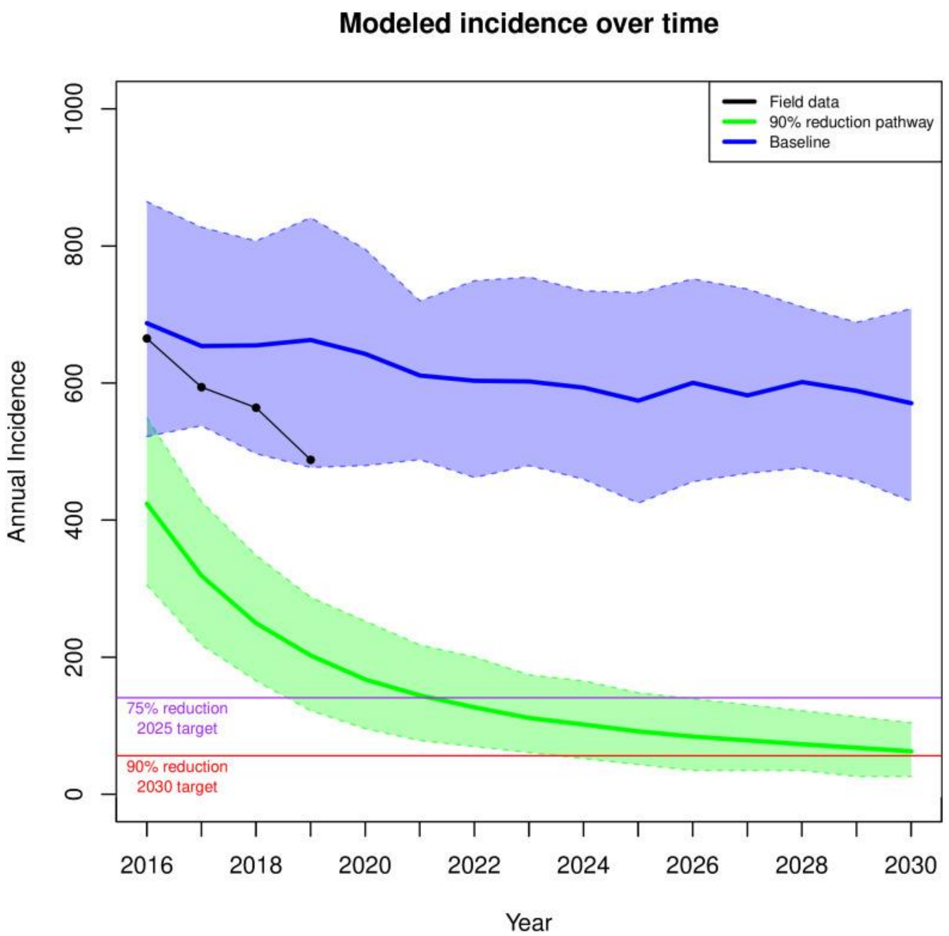
- Complex models with more parameters that need to be specified often from different data sources, which could impact our model findings.
- In practice, these models are calibrated to real-world data, for example, using outcome prevalence estimates.
- Sensitivity analyses are performed for key parameters or parameters with known uncertainty.
- Computational time can be burdensome; however, high-performance computing, including parallel processing, can reduce computational time.

ABM Example

ABMs—Levers of HIV Model (LHM)

- An agent-based model, to simulate and evaluate the impact of various HIV prevention and treatment strategies on reducing new HIV infections among men who have sex with men (MSM) in Chicago (Vermeer et al. 2022)
- Simulated a 15-year period (2016–2030) encompassing 2,304 distinct scenarios.
- Incorporated six key "levers" influencing HIV prevention and care (PrEP, ART: linkage, retention; PrEP adherence; viral suppression)
- Optimal scenarios achieving a 90% reduction in new HIV infections by 2030 required: Highest levels of ART retention and PrEP adherence; Near-highest levels of PrEP retention; Moderate levels of PrEP linkage.
- Under current trends (2016–2019), the projected reduction in new HIV infections falls short of the 90% target by 2030 (p = 0.0006).

ABMs—High Impact Example (2)



Vermeer et al. 2022

Lab Exercises

1. Modify the code above so that it takes 28 days to adopt (if exposed) and 48 days to lose weight if exposed/adopted. What happens to the output figure?
2. Modify the number of contacts per day to 20 contacts. What happens to the output figure? Be sure to regenerate the baseline data using the original specifications, so we can compare to the baseline scenario.
3. Vary the probability of transition from susceptible to exposed from 0.05 to 0.10. What happens to the output figure? Be sure to reset the weekly contact rate to 3 contacts.

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