

¹ FacilityEpiSim: an agent-based simulation package for infectious disease transmission in healthcare facilities

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Software

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⁶ Summary

⁷ Mathematical modeling of healthcare-associated infection (HAI) epidemiology is a useful tool for addressing infections acquired during medical care, which cause significant morbidity, mortality, and financial strain on health systems worldwide. HAIs arise from complex interactions among patients, healthcare workers, the clinical environment, and microbial evolution. Because these interconnected processes are difficult to observe in real-world or experimental settings, models provide a powerful, risk-free way to understand how infections spread and how interventions may reduce transmission. We developed FacilityEpiSim, a continuous-time, agent-based simulation model of infectious disease transmission in healthcare facilities. The software tool allows modelers and their public health collaborators to run simulations to study transmission dynamics among facility patients and evaluate the utility of patient surveillance strategies before implementing them.

¹⁸ Statement of need

¹⁹ The tool is an agent-based model (ABM) built with Repast Simphony 2.11.0 (North et al. [\(2013\)](#)) for simulating transmission of an infectious organism in a healthcare facility. The model ²⁰ simulates flow of inpatients or residents of the facility over a specified time period, tracking ²¹ patient admissions, lengths of stay, and discharges, disease importation and transmission ²² dynamics, clinical detection and active surveillance testing with isolation of detected patients ²³ serving to partially decrease transmission. Patients in a susceptible state move to a colonized ²⁴ (i.e., infected) state at a rate proportional to the number of colonized patients currently in ²⁵ the facility, with detected colonized patients transmitting at a discounted rate according to ²⁶ the assumed isolation effectiveness. Undetected colonized patients can progress to clinical ²⁷ detection (i.e. a positive test driven by symptomatic, clinical infection) or can spontaneously ²⁸ return to a susceptible state upon decolonization.

²⁹ The main intervention that can be tested in the simulation is active surveillance, which can ³⁰ occur at admission and/or at regular intervals during a patient's stay in the facility, with ³¹ configurable adherence rates, test sensitivity, and durations between mid-stay tests. Active ³² surveillance can identify asymptotically colonized patients who would not otherwise have ³³ been detected and reduce transmission according to a configurable isolation effectiveness ³⁴ parameter. A non open-source version of our code was used to generate results for three prior ³⁵ publications: Slayton et al. [\(2015\)](#), Toth et al. [\(2017\)](#), and Toth et al. [\(2020\)](#). These studies ³⁶ demonstrated the utility of this simulation model for generating novel insights for public health.

³⁷ With this open source version of our model, users can now configure simulation settings to ³⁸ particular facilities, infectious organisms, and surveillance intervention strategies of interest ³⁹ ([Figure 1](#)). The code generates time series outputs, event logs for admissions, transmissions, ⁴⁰ detections, etc., and can also perform batch runs with parameter sweeps to test a range of ⁴¹

42 assumptions or surveillance strategies. We also provide R scripts that analyze raw simulation
 43 output to verify model behaviors and view sensitivity analysis results. These capabilities will
 44 allow users to extend our prior, published research findings and generate new insights for public
 45 health.

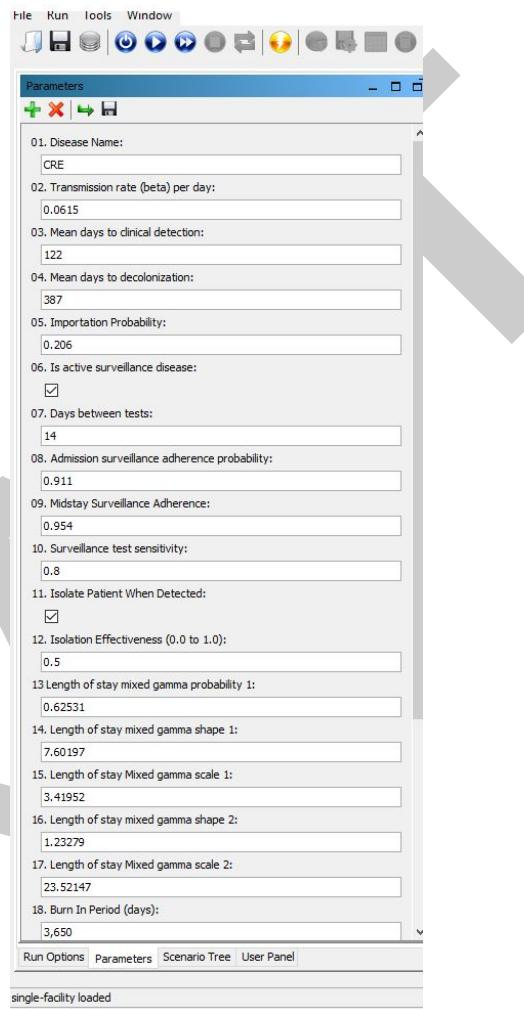


Figure 1: Parameters panel available when running the non-batch version of the simulation in Repast Simphony.

46 While several open source software packages exist for general infectious disease outbreak
 47 simulation (e.g., Jeness et al. (2013), Gozzi et al. (2025), Lorton et al. (2019), Grefenstette
 48 et al. (2013), Gallagher et al. (2024), Meyer & Yon (2023)), none of these provide settings
 49 specific to healthcare facility epidemiological scenarios without significant customization efforts
 50 by the user. We found one public repository, H-outbreak, for spatial-temporal simulation for
 51 hospital infection spread (Kim et al. (2023)), which emphasizes modeling spatial hospital layout
 52 and staffing rather than transmission dynamics and surveillance. Furthermore, to our knowledge
 53 all these existing simulation models use discrete time steps rather than the continuous-time,
 54 event-based framework implemented in our model, which obviates the need for choosing a
 55 time step frequency that could unintentionally affect simulation dynamics.

56 AI Usage Disclosure

57 Generative AI was used in the creation of this project. Tools used include GitHub Copilot,
58 Copilot Agents, and Claude Code. A variety of models were used with each tool, including
59 Sonnet 4.5, Opus 4.5, GPT 4, GPT 5 and GPT-5 mini. These were used primarily in the creation
60 of code and documentation. AI assisted in the generation of code, debugging, bootstrapping
61 data analysis, scaffolding for documentation and some documentation generation. The authors
62 of this paper assert that human authors reviewed, edited and validated all AI-assisted outputs
63 and made the core design decisions.

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