# An Alternative Paradigm for Digital Exposure Notification: Detecting Super-spreading Events

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# Overview

- **Motivation**
  - Much of COVID-19 spread is attributable to super-spreading events*, where aerosolized virus can accumulate and permeate a room due to poor ventilation
  - Current GAEN/TC4TL paradigm does not capture most of these infections, e.g., because they are not close enough or index case does not have the app
- **Idea**
  - Send an exposure notification if the user spent a significant amount of time in the simultaneous presence of multiple others who later report a positive test
  - Threshold based on an a posteriori estimate of likelihood the user got infected
- **Properties**
  - Works within the GAEN system but fundamentally changes configuration of the "attenuation" and "days" parameters and criteria for sending a notification
  - Targets high-impact events: the more people, the greater the statistical power
  - Linear dependence on adoption rate: works even if index case not using app
  - Implicitly captures transmission factors GAEN cannot: biological, situational

*E.g., see Goyal et al. (2020)

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# GAEN Configuration — Comparison to Current Paradigm

| Parameter | Description | Configuration under current paradigm | Configuration under new paradigm | Motivation/Rationale |
|---|---|---|---|---|
| **Days** | # of days prior to positive test or symptom onset | High score if at most 2 days; based on **infectiousness curve** | High score if at least 3 days; based on **incubation period** | Current paradigm considers whether the person was infectious at the time of contact; new paradigm considers whether the person got infected then |
| **Attenuation** | Bluetooth signal attenuation; proxy for distance | High score if estimated to be **within 6 feet** | High score if estimated to be **within 30 feet** | Current paradigm considers whether an infectious person was in close contact; new paradigm considers whether people who later got infected were in the same room |
| **Duration** | Duration of contact | High score if at least 15 minutes | High score if at least 30 minutes | Current paradigm based on “plume” model of transmission during close contact; new paradigm considers “room” model where virus-laden aerosols accumulate in the air |
| **Notification criteria** | When to send a notification to the app user | **“Too close for too long” contact with an infected person** | **Nearby multiple others who likely got infected around that time** | Current paradigm considers whether the app user got infected by a specific person; new paradigm flags when the user was present at a likely super-spreading event |

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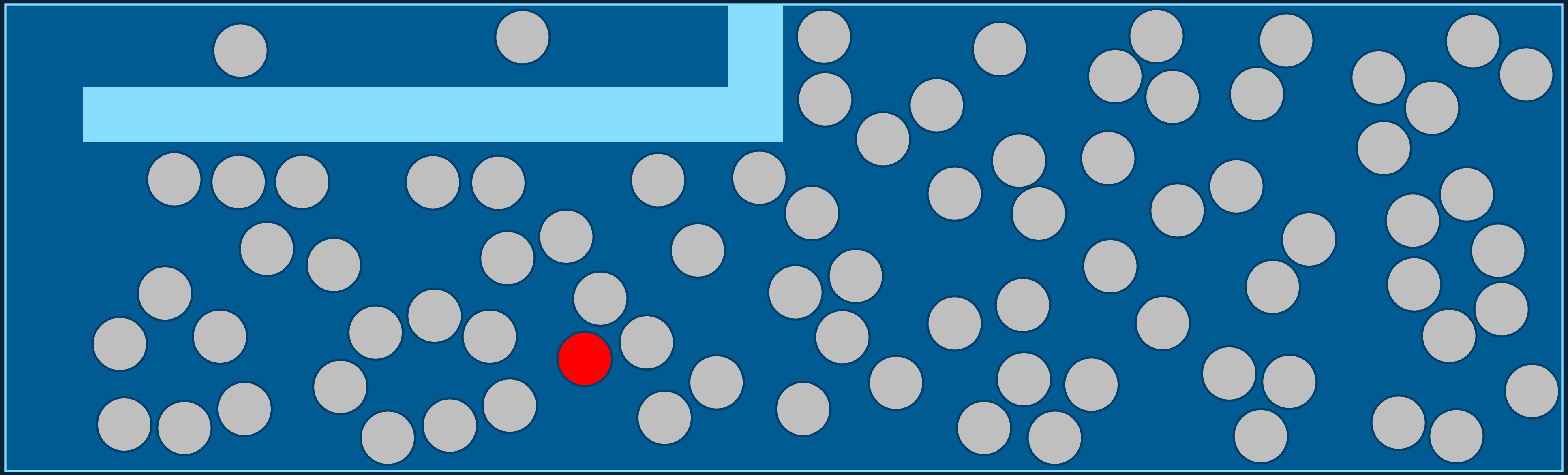
# Example Scenario

- 80 people in a bar with a highly infectious person who does not have the app



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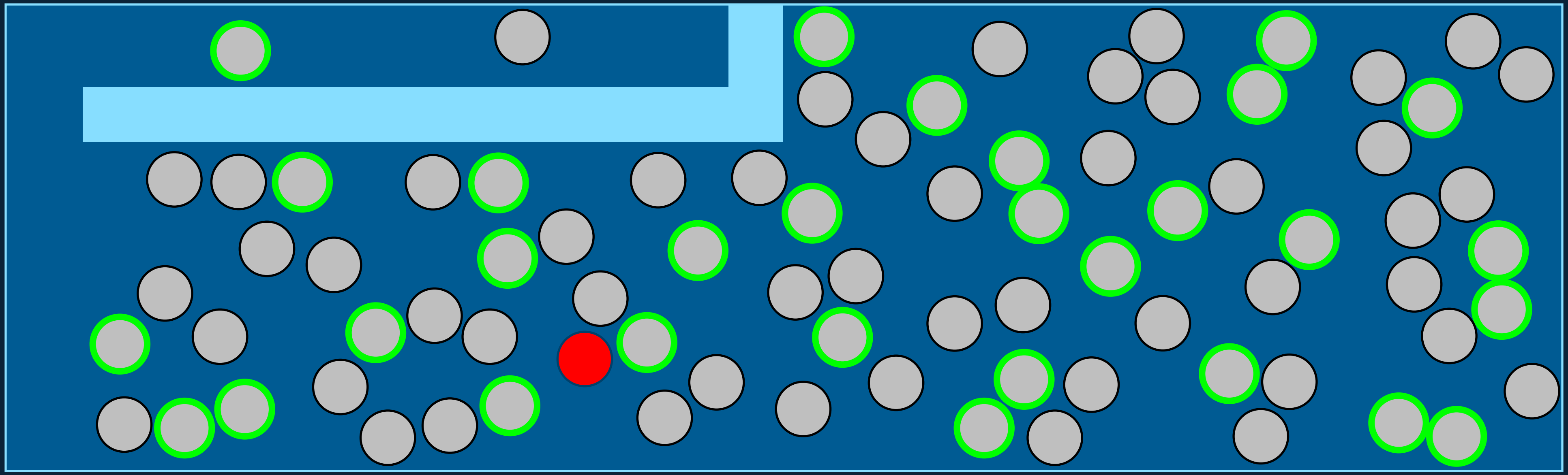
# Example Scenario

- 80 people in a bar with a highly infectious person who does not have the app
- 30 of the 80 susceptible people are app users (38% adoption rate)



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- 80 people in a bar with a highly infectious person who does not have the app
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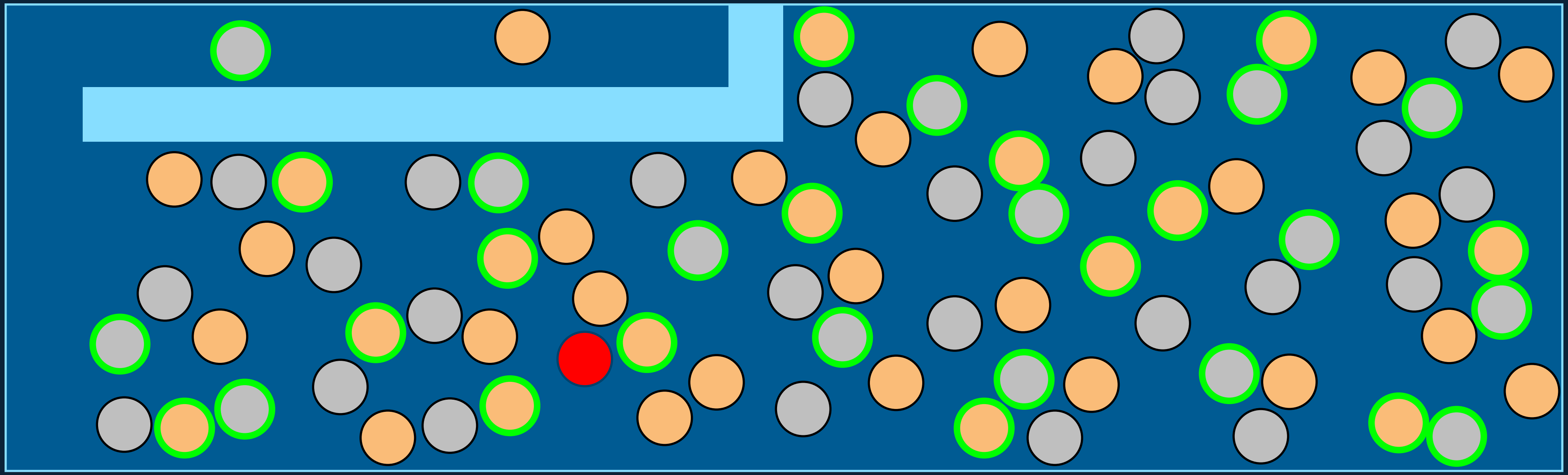
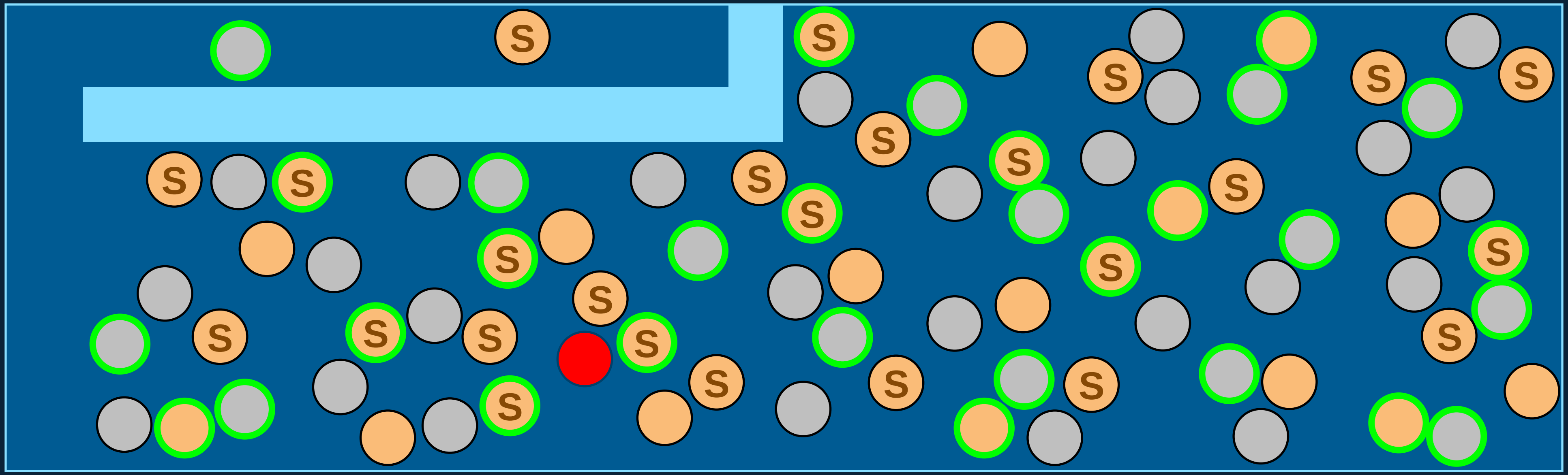
- 40 people get infected, including 15 app users



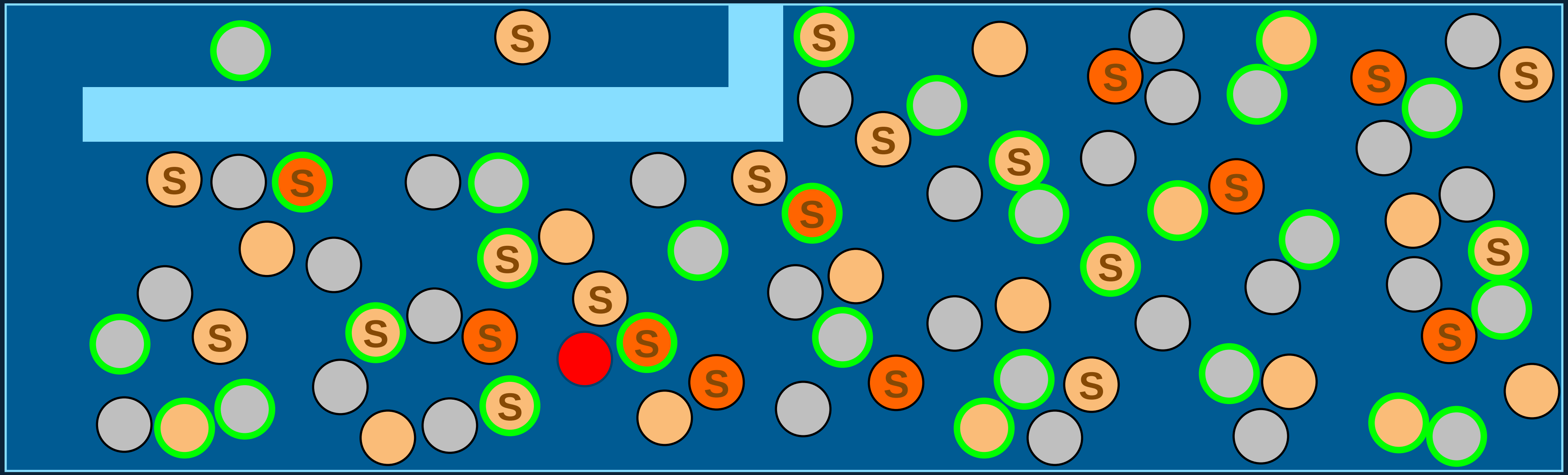
# Example Scenario

- 80 people in a bar with a highly infectious person who does not have the app
- 30 of the 80 susceptible people are app users (38% adoption rate)
- 40 people get infected, including 15 app users
- 25 of those infected eventually become symptomatic, including 10 app users



# Example Scenario — Outcome

- Current paradigm: **Nobody gets notified** because the infectious person does not have the app and others were not infectious at the time

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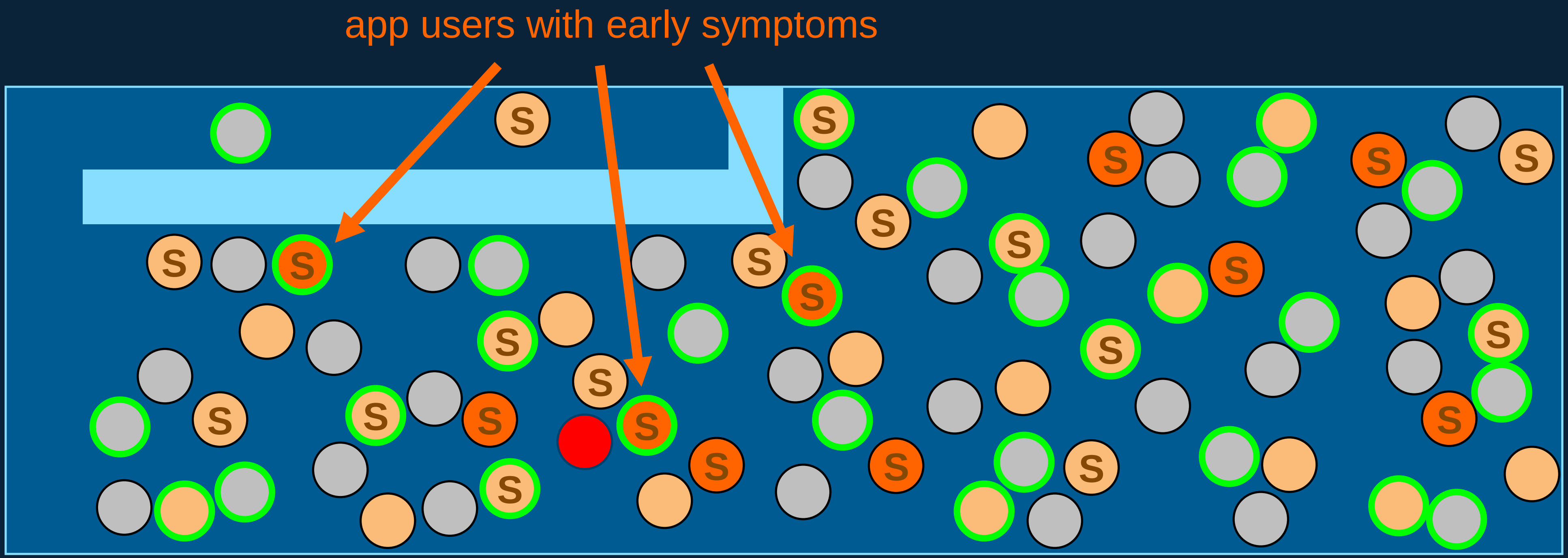
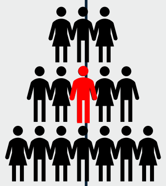
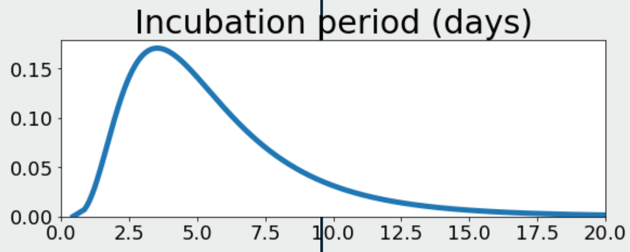
# Example Scenario — Outcome

- Current paradigm: **Nobody gets notified** because the infectious person does not have the app and others were not infectious at the time
- New paradigm: After the first 3 symptomatic app users report a positive test via the app, the other **27 app users get notified, 12 of whom were infected**



# Example Scenario — Timeline

| Sunday | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday |
|---|---|---|---|---|---|---|
| | | | | | Day 0<br>**Super-spreading event**  | Day 1 |
| Day 2 | Day 3<br>**Early symptom onset for first 30% of symptomatic secondary cases** | Day 4 | Day 5<br>**Early symptom testing** | Day 6 | Day 7<br>**Test results → exposure notifications** | Day 8 |
| Day 9 | **Estimated 26%* of symptomatic secondary cases will still be pre-symptomatic 7 days after getting infected — those are the people most likely to spread the virus the following weekend** | | | |   | |

*Based on maximum likelihood estimate of incubation period distribution by [Ferretti et al. (2020)]

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# Vision

- **GAEN could provide users with several different notification types, each with appropriate messaging/recommendations:**
  - **Close contact with infected person, low likelihood of transmission**
    - Inform user of exposure to raise awareness and motivate behavior change
  - **Close contact with infected person, high likelihood of transmission**
    - Inform user of exposure, recommend testing and/or self-quarantine
  - **Attendance at likely super-spreading event**
    - Inform user of exposure, recommend testing and/or self-quarantine

# Next Steps

- **Assess the feasibility and efficacy of the new paradigm**
  - Can it notify enough people early enough to significantly reduce spread?
  - How does its precision-recall tradeoff compare to the current paradigm?
- **Estimate impact on population-level health outcomes and social burden**
  - Building on Oxford's open-source agent-based simulation model to include super-spreading events, both observed and unobserved factors in viral transmission, and explicit representation of contact tracing mechanisms
  - Consider new paradigm as alternative and complement to current paradigm
- **Collaborate with others to reduce the spread of COVID-19**
  - Explore the technical and operational challenges involved in adapting GAEN for super-spreading event detection
  - Integrate our changes into Oxford's open-source repository for public use
  - Help inform PHAs in determining messaging around exposure notifications

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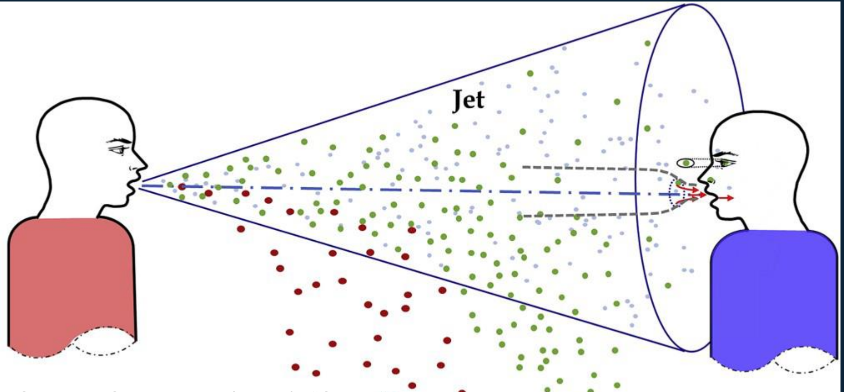
# BACKUP

# Efficacy of GAEN — Study Design

- **Simulate interactions** between infected and susceptible users of GAEN-based apps, then use the GAEN risk formula to infer whether transmission occurred
  - Transmission model integrates components from established and recent literature: infectiousness, emission, transport, and dose-response models
  - Consider both observed and unobserved biological and situational factors
- **Measure efficacy** as GAEN’s ability to achieve both high recall (detection rate of true transmission events) and high precision (low false alarm/notification rate)
  - Evaluate under both ideal and noisy conditions (e.g., attenuation -> distance)




Source: Chen et al. (2020). “Short-range airborne route dominates exposure of respiratory infection during close contact”. *Building and Environment*.

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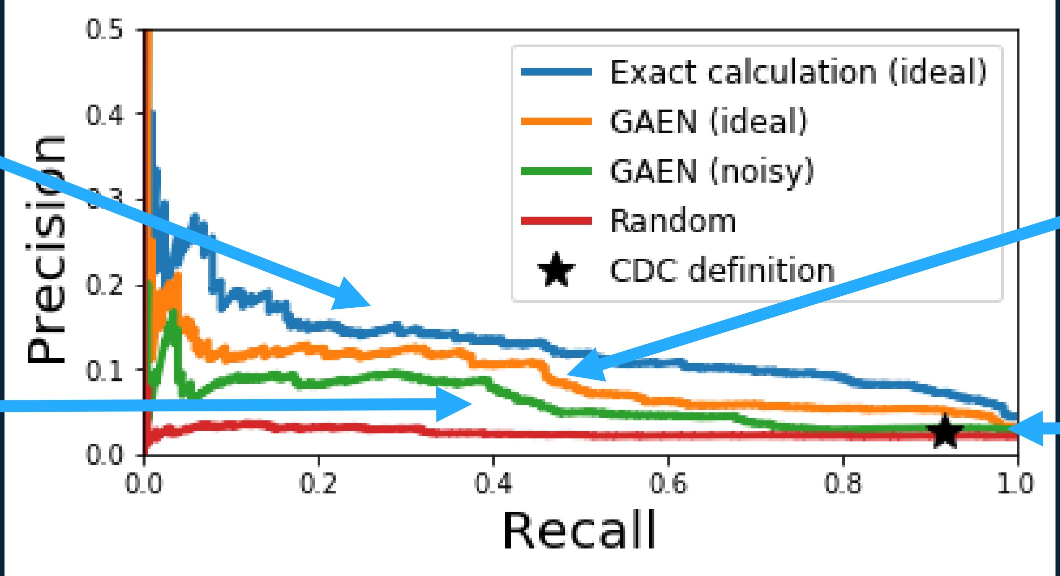
# Efficacy of GAEN — Study Conclusions

- **Fundamental limit on GAEN's ability to accurately predict transmission** Detecting 50% of transmissions means that more than 90% of exposure notifications will be false alarms — even if GAEN perfectly infers distance, duration, and days — which may drive down app usage and compliance
- **New solutions must break out of the current paradigm** if a more favorable precision-recall tradeoff is to be achieved

Precise formula using observable factors captured by GAEN

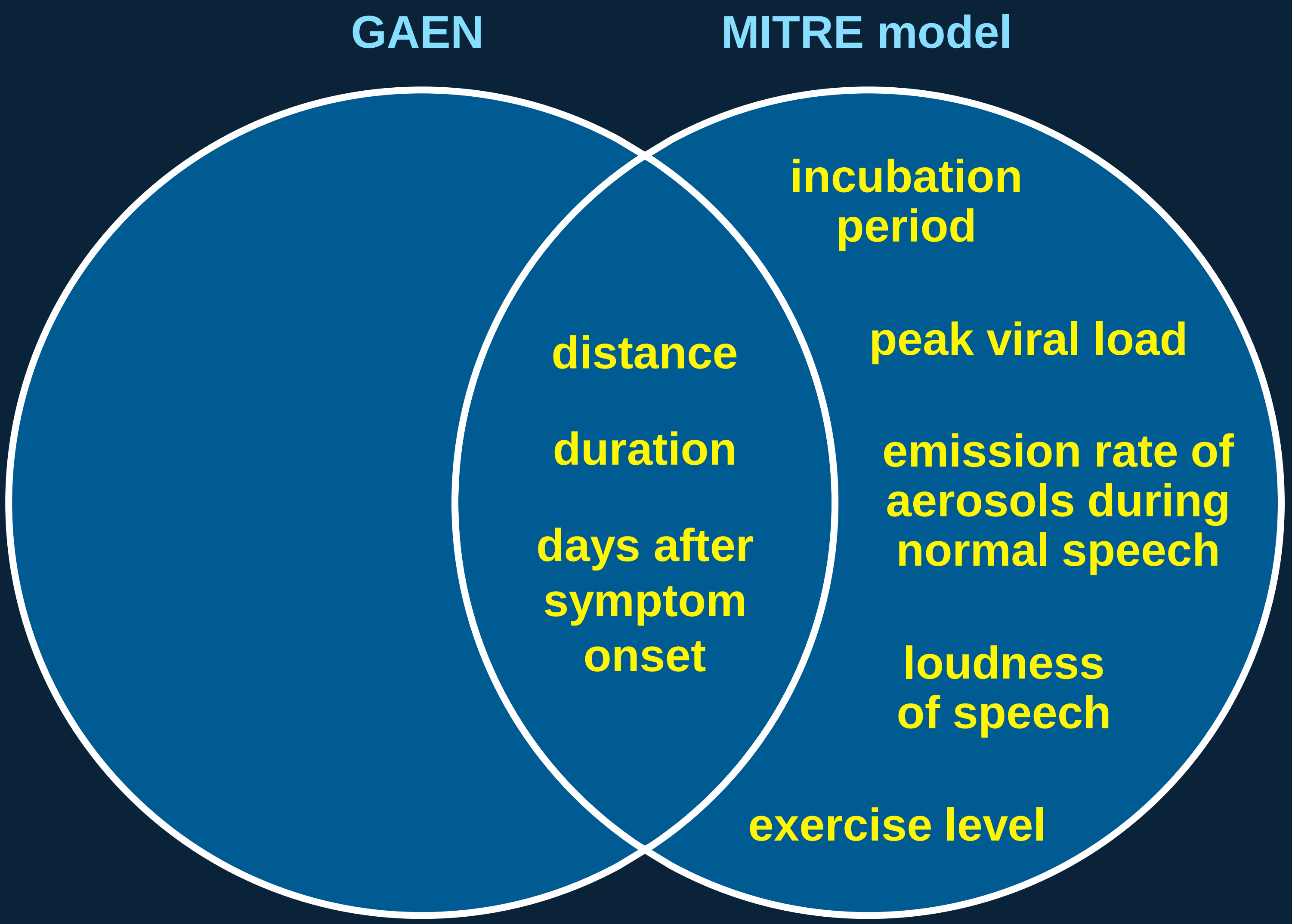
GAEN under noisy conditions, using recommended configuration




GAEN under ideal conditions, using recommended configuration

Manual contact tracing, assumes perfect memory and doesn't work for strangers

# Efficacy of GAEN — Transmission Factors Considered

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# Efficacy of GAEN — Impact of Transmission Factors

| Transmission Factor | Used by GAEN? | How to infer | Accuracy | Impact on effectiveness |
|---|---|---|---|---|
| **Who (person)** | No | Only evident in retrospect if many infections result | Moderate with data on forward-traced infections, low otherwise | **High** — maximum amount of virus transmitted can vary by multiple orders of magnitude across individuals [Jacot et al. (2020), Asadi et al. (2020)] |
| **What (activity)** | No | Assumption based on environment | Moderate with location data (bar vs. restaurant vs. train), low otherwise | **High** — amount of virus transmitted can vary by over two orders of magnitude from breathing to singing or shouting [Morawska et al. (2009), Asadi et al. (2020)] |
| **Where (environment)** | No | Location data, RSSI/sensors for indoor/outdoor | High with location data, moderate with sensor data, low otherwise | **Moderate** — size of space is helpful for identifying super-spreading events, less important for tracing individual contact events except for indoor/outdoor |
| **When (time)** | Yes | date of self-report or + test, proxy for symptom onset | Moderate if infected person is symptomatic, low otherwise | **High** — amount of viable virus transmitted decreases by multiple orders of magnitude if more than 1-3 days before or after the time of peak infectiousness |
| **How close/crowded (proximity)** | Yes | Bluetooth RSSI and/or other sensor data | High with sensor data, moderate with RSSI only | **Moderate** — high accuracy is helpful for tracing individual contacts; moderate accuracy is probably sufficient for identifying super-spreading events |
| **How long (duration)** | Yes | Timestamps of scans when ID appeared | High (within 5 minutes) | **Moderate** — amount of virus transmitted grows between linearly and quadratically with duration, depending on ventilation rate and other factors |

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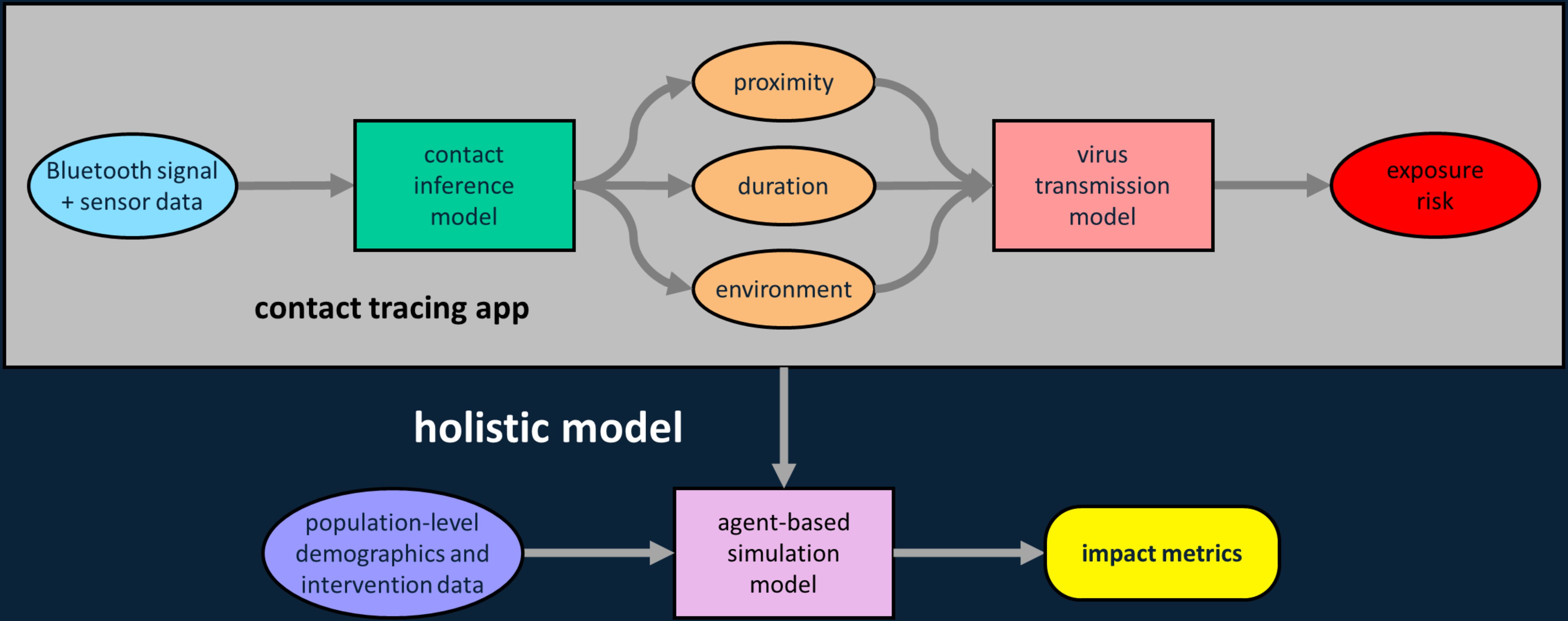
# Measuring Impact — Integration with Oxford model *

- **What is the Oxford model?**
  - **Population-level agent-based simulation model** capturing demographics, person-to-person interactions, virus spread, NPIs, and health outcomes
  - Developed at Oxford Big Data Institute, published in Science, open-source
- **Proposed augmentations to the Oxford model:**
  - **Group interactions** — many people in an enclosed space for a prolonged period of time (bars, public transit, etc.); "room" model vs. "plume" model; enables modeling of super-spreader events
  - **Contact tracing apps** — higher-fidelity model enables comparison of effectiveness of different exposure risk inference algorithms

* Hinch et al. (2020). "COVID-19 Agent-based Model With Instantaneous Contact Tracing".
Open-source code repository: [https://github.com/BDI-pathogens/OpenABM-Covid19](https://github.com/BDI-pathogens/OpenABM-Covid19)

# Measuring Impact — Integration with Oxford model

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