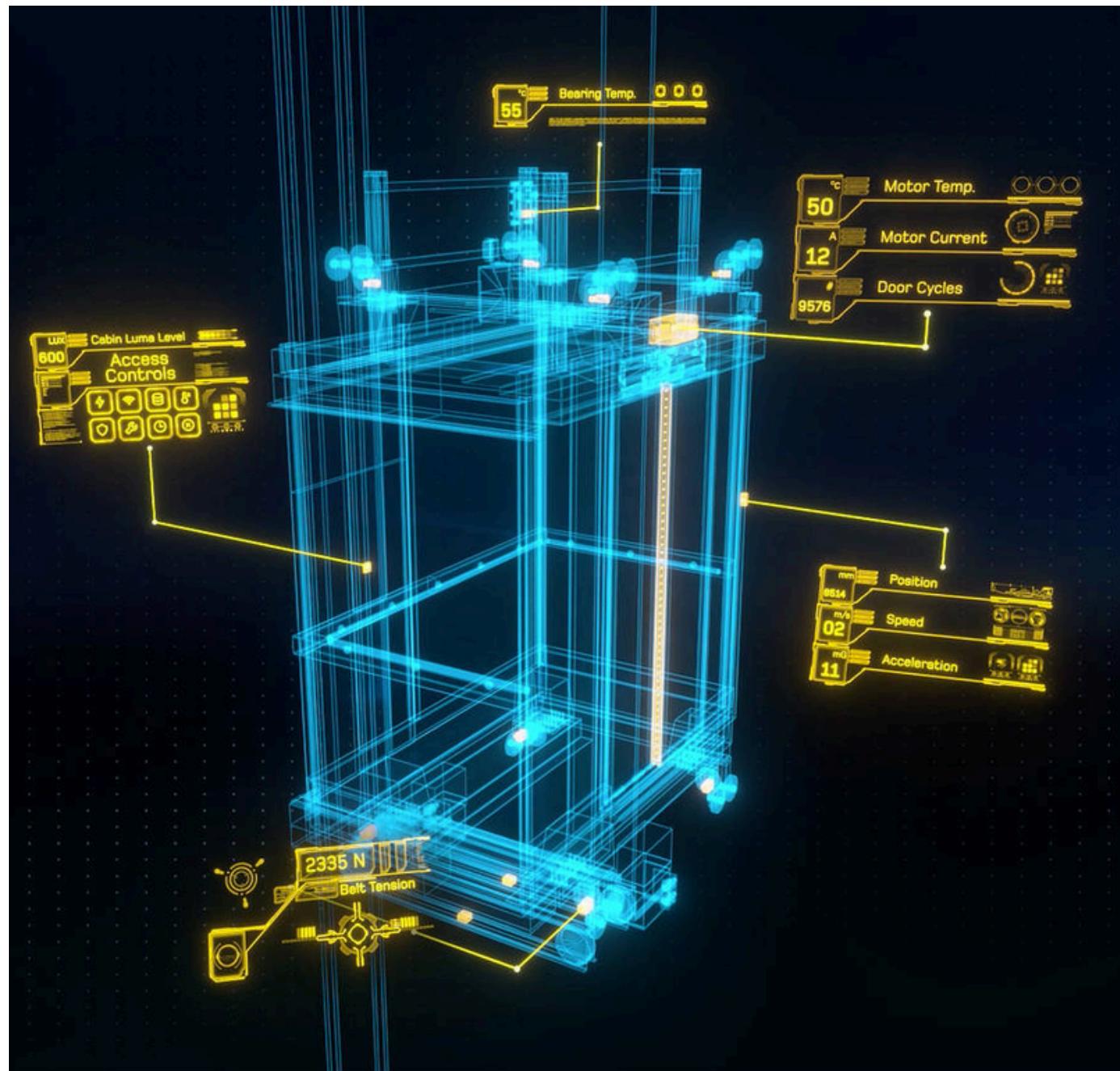




# Digital Twins in Infection Risk Modelling

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2. Design of the Digital Twins System
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# Background & Motivation

# Background & Motivation

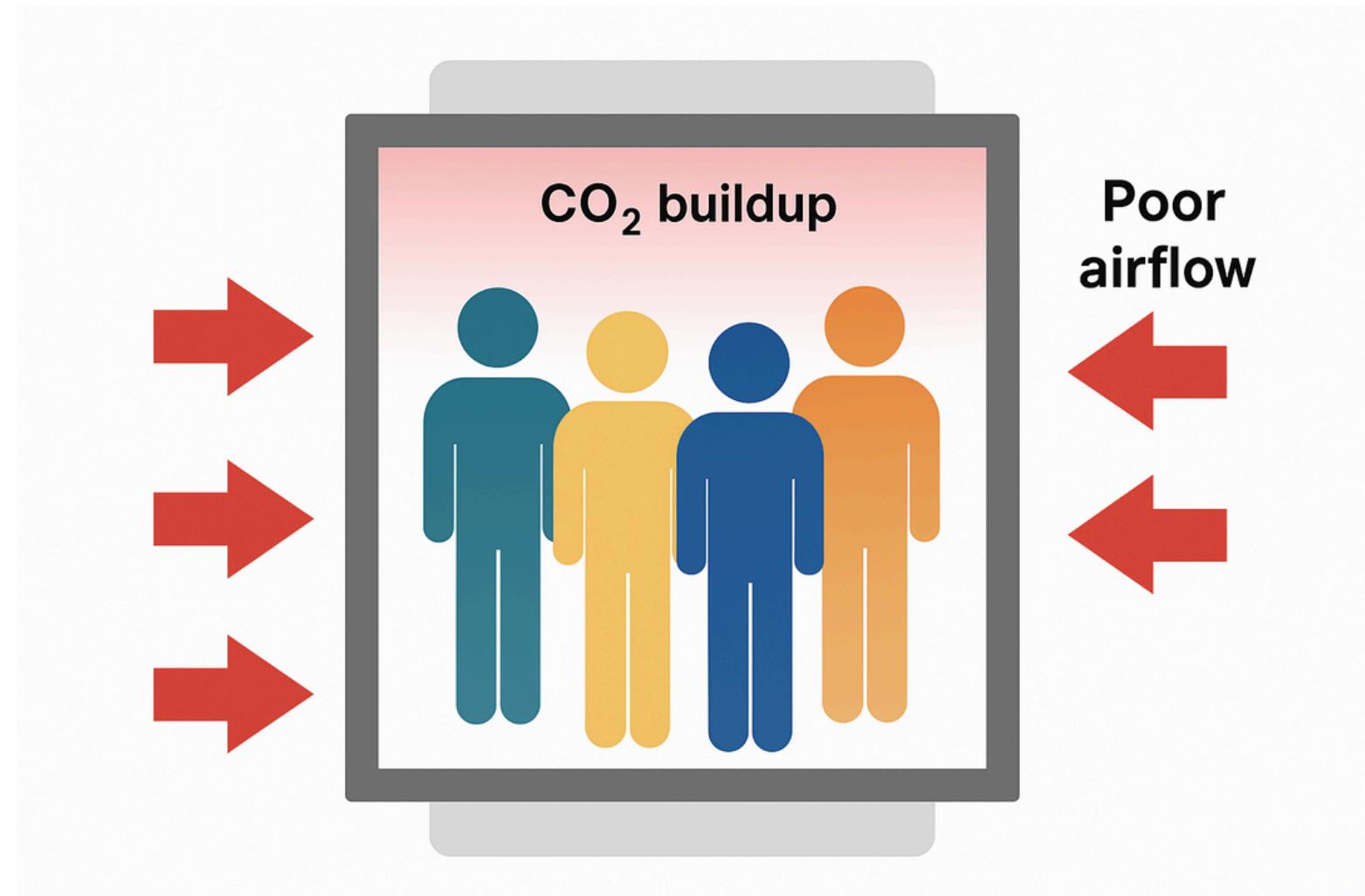
## Lifts: High-Risk Zones for Airborne Transmission

**Confined Volume:** Enclosed cabin space typically ranges from 3–5 m<sup>3</sup>, leaving limited room for air dilution.

**Frequent Use:** Elevators experience high occupancy turnover, often used dozens of times per hour by different individuals.

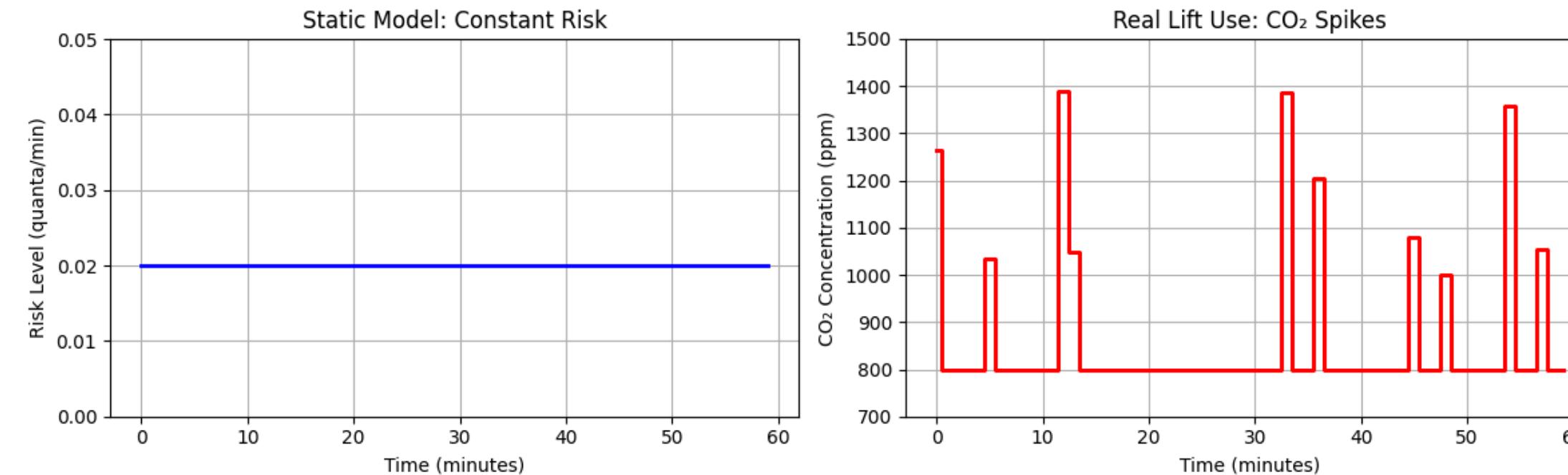
**Poor Ventilation:** Ventilation is usually passive or shaft-dependent, leading to limited fresh air exchange.

**Short but Intense Exposure:** While trips are brief, passengers are nearby, and CO<sub>2</sub> and aerosol buildup can spike rapidly between rides.



# Static Models Fall Short

Comparison: Static Model vs Real Elevator Use



\*The graphs use **simulated data** to conceptually illustrate differences between static models and real elevator use. They do not reflect actual sensor readings.

## Limitations of Traditional Risk Models

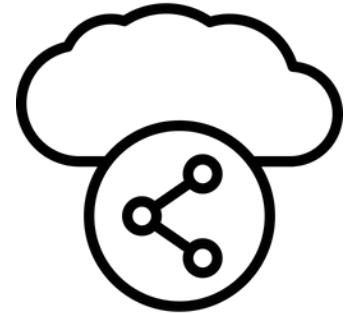
**Assume Average Conditions:** Uses fixed occupancy and ventilation values.

**Miss Short-Term Spikes:** Fails to detect short-term risk surges (e.g., post-lecture crowds).

**Delayed Risk Detection:** Delays in identifying high-risk moments.

**Pathogen-Agnostic Assumptions:** Doesn't adapt to different disease transmission rates.

# Bridging the Gap: Real-Time, Affordable Risk Detection



## Real-Time Data

Continuously monitor CO<sub>2</sub>, temperature, and humidity to reflect real-time environmental conditions inside lifts.



## Disease-aware modelling

Dynamically update infection risk based on changing occupancy and ventilation levels.



## Alerts

Scale effortlessly across multiple lifts and buildings without heavy infrastructure.



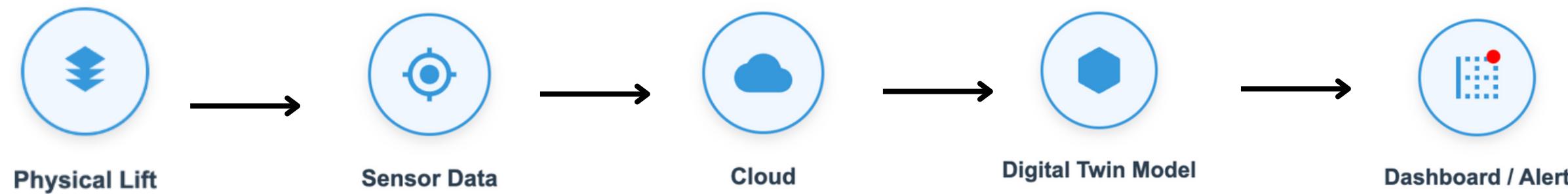
## Low-Cost

Operate on low-cost hardware, avoiding reliance on expensive or proprietary IoT ecosystems.

# The Digital Twin Solution

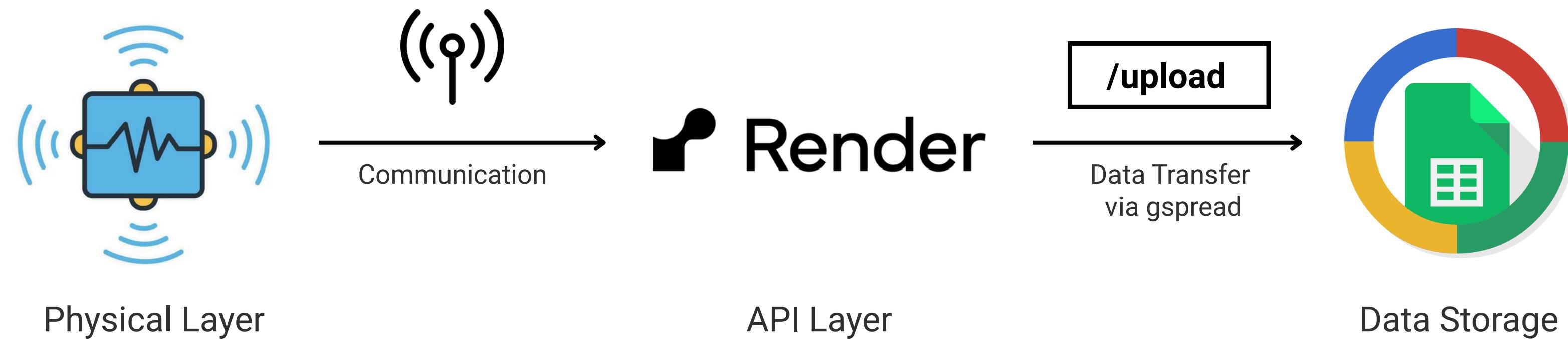
“A digital twin is a virtual representation of a connected physical asset and encompasses its entire product lifecycle.”

-*Digital Twin: Definition & Value – An AIAA and AIA Position Paper*



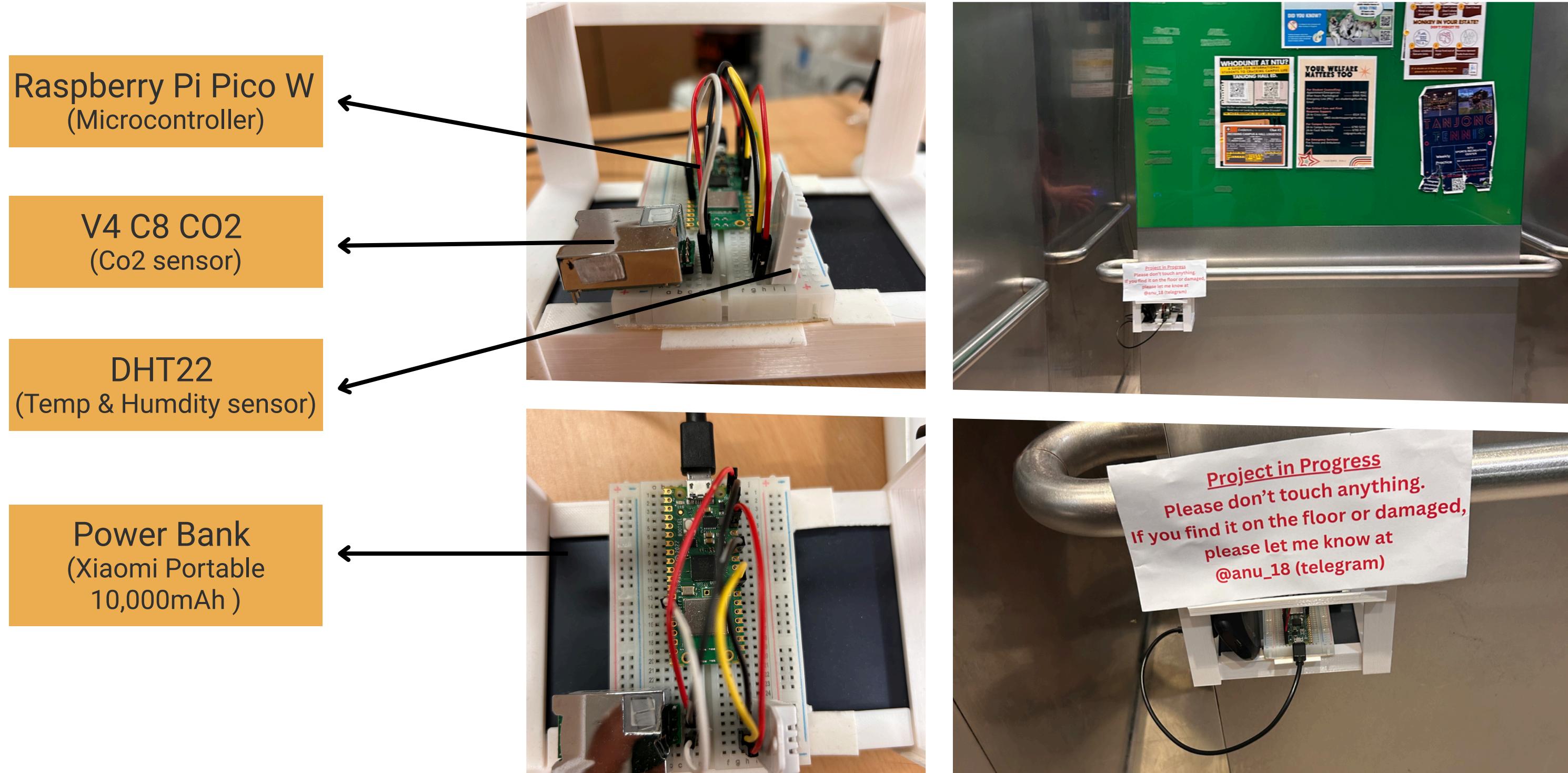
# Design of the Digital Twins System

# Designing the Digital Twin Architecture



\*This is my setup for the digital twins in the lift.

# Deploying the System in a Real Lift



# Infection Risk Modelling

# Epidemiology Meets Engineering

## Wells-Riley Equation

$$P = 1 - e^{\left(\frac{-Ipqt}{Q}\right)}$$

$I$ : Number of infectious individuals  
 $q$ : Quanta generation rate (disease-dependent)  
 $p$ : Breathing rate of susceptible individuals  
 $t$ : Exposure duration  
 $Q$ : Room ventilation rate (in volume/time)

### Assumption:

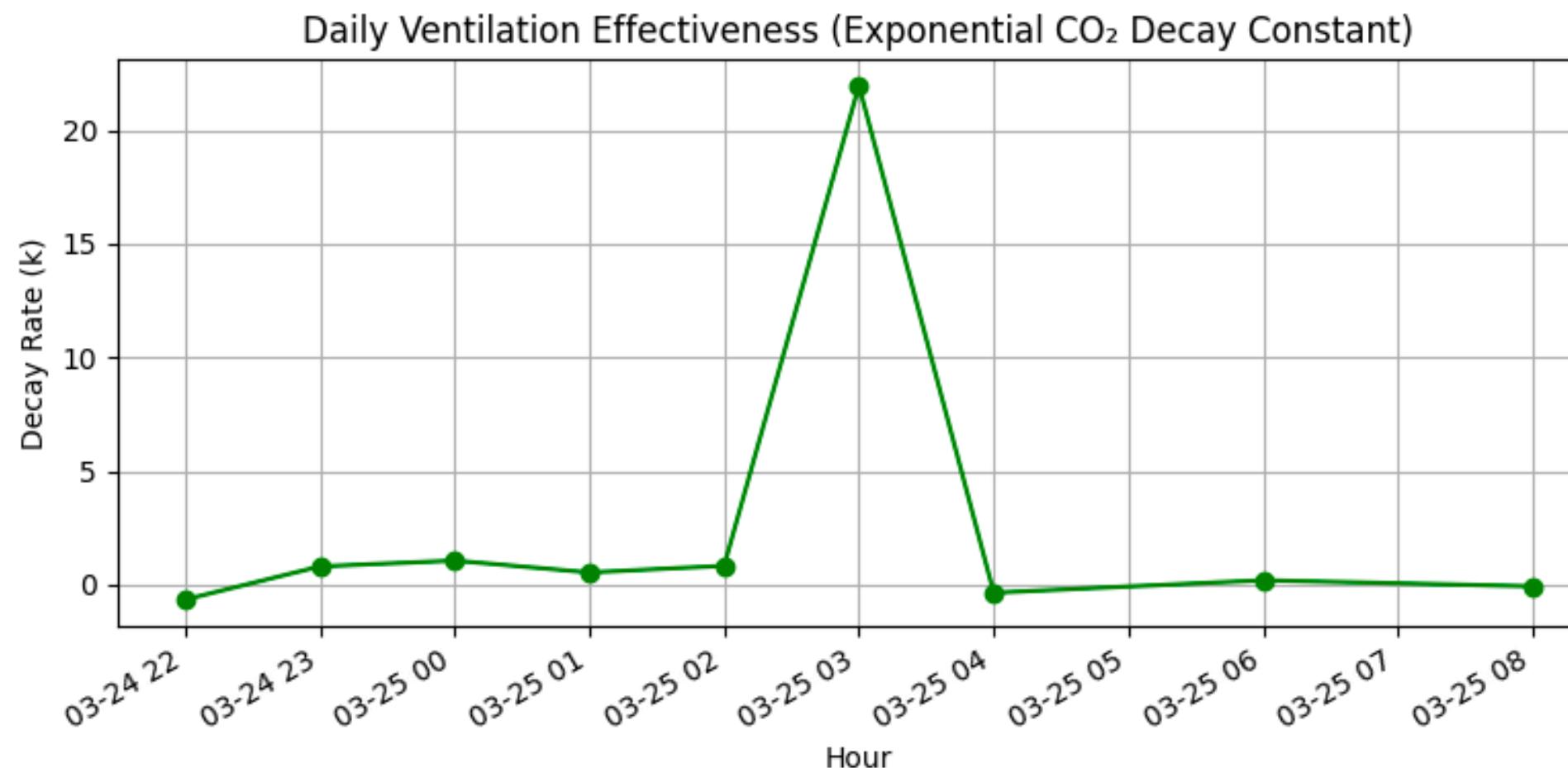
$I = 1$ : Assumes at least one infected individual is present in the lift.

**q (Quanta Generation Rate):** Values taken from peer-reviewed research for COVID-19, Measles, and TB.

**p (Pulmonary Ventilation Rate):** Based on average breathing rate of a resting adult.

**t (Exposure Time):** Calculated from sensor logs; an average duration per lift ride was used.

# From CO<sub>2</sub> Decay to Ventilation Rate: How Q is Calculated



CO<sub>2</sub> decays exponentially post occupancy

Fitted using:

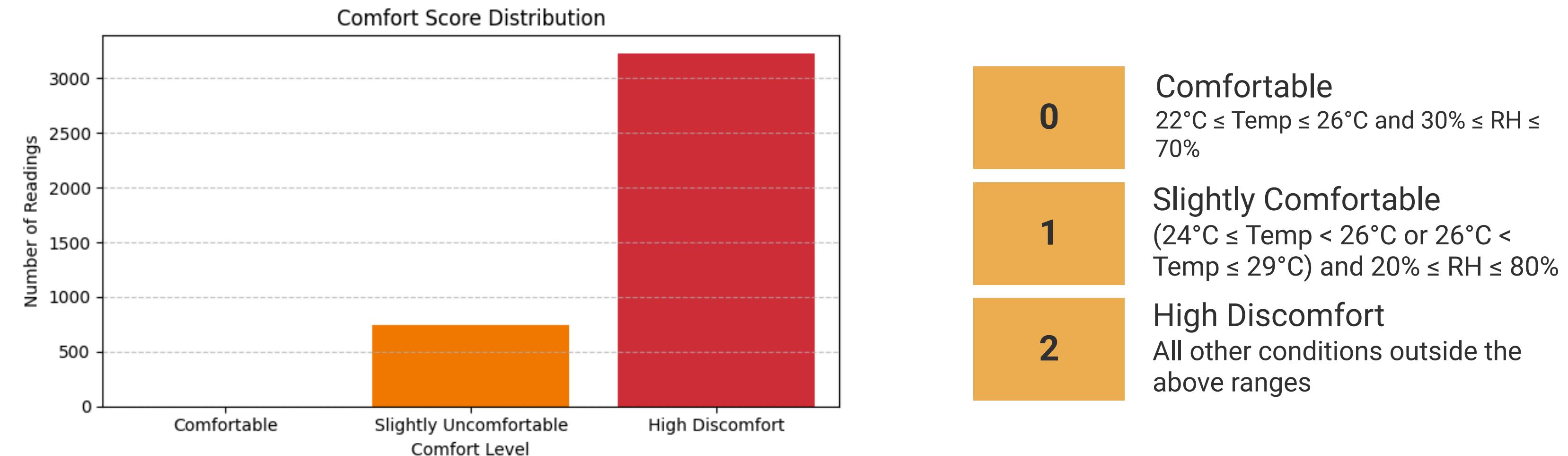
$$C(t) = C_0 \times e^{(-k \times t)} + C_t$$

Air changes per hour (ACH) derived from k

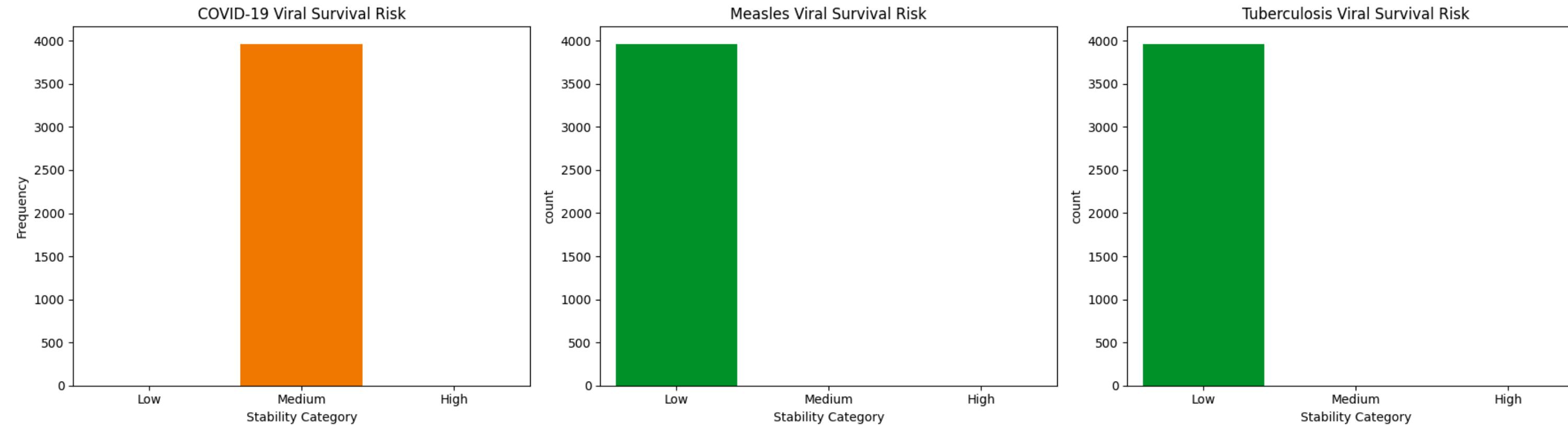
Enables real-time estimation of Q, no airflow sensor required

Good fit = fast decay → better ventilation

# Balancing Safety and Comfort: VESS and ASHRAE Scoring



# Balancing Safety and Comfort: VESS and ASHRAE Scoring



Low

Temp  $\geq 20^{\circ}\text{C}$  and  $40\% \leq \text{RH} \leq 60\%$

Med

**Temp  $< 20^{\circ}\text{C}$  or RH  $< 40\%$  or  $> 60\%$**

High

Temp  $< 21^{\circ}\text{C}$  and RH  $< 50\%$

**Temp  $\geq 21^{\circ}\text{C}$  and RH  $\geq 50\%$**

Temp  $< 21^{\circ}\text{C}$  or RH  $< 50\%$

**Temp  $\geq 25^{\circ}\text{C}$  and RH  $\geq 50\%$**

Temp  $< 25^{\circ}\text{C}$  or RH  $< 50\%$

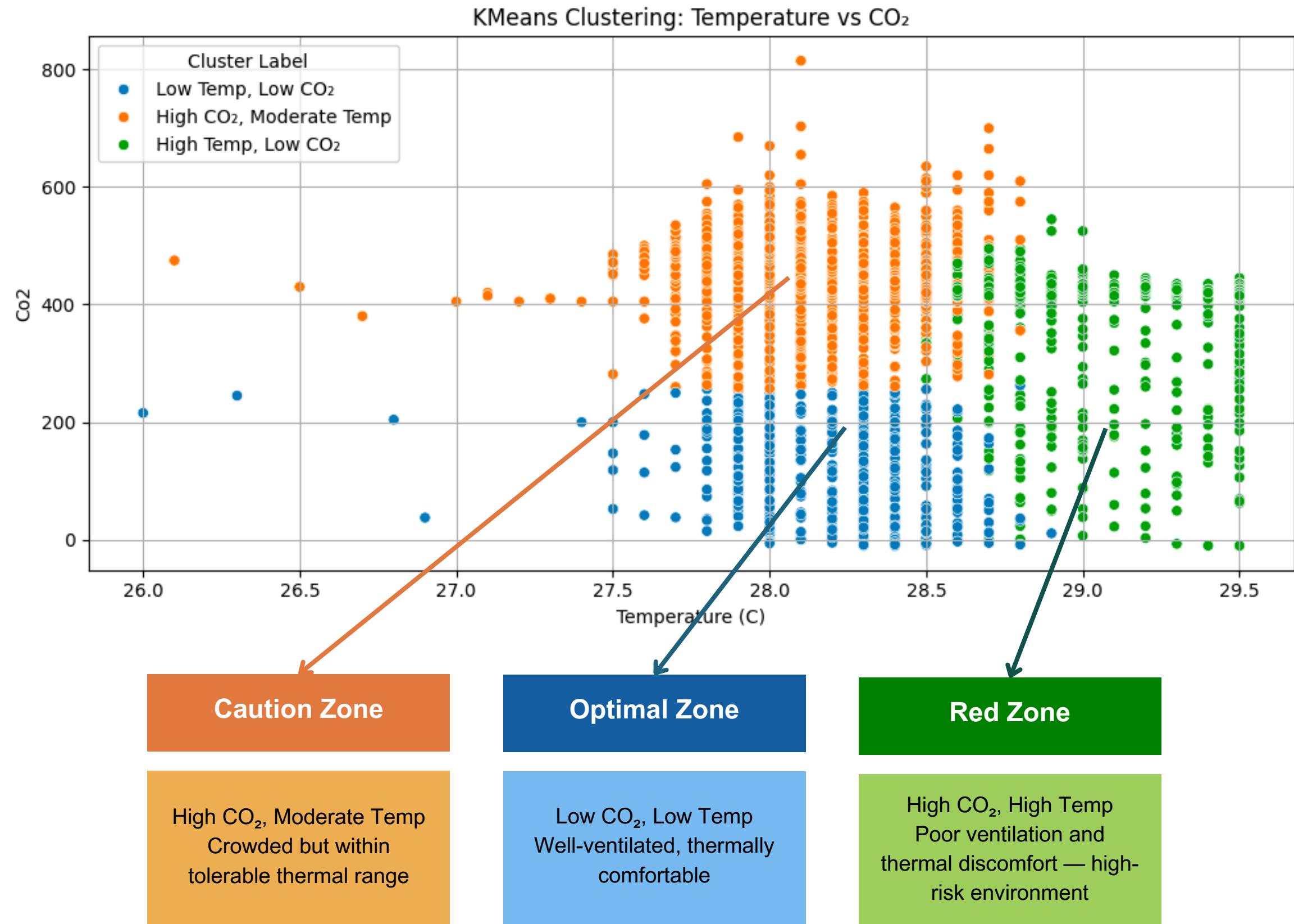
Temp  $< 25^{\circ}\text{C}$  and RH  $< 50\%$

# Machine Learning & their Roles

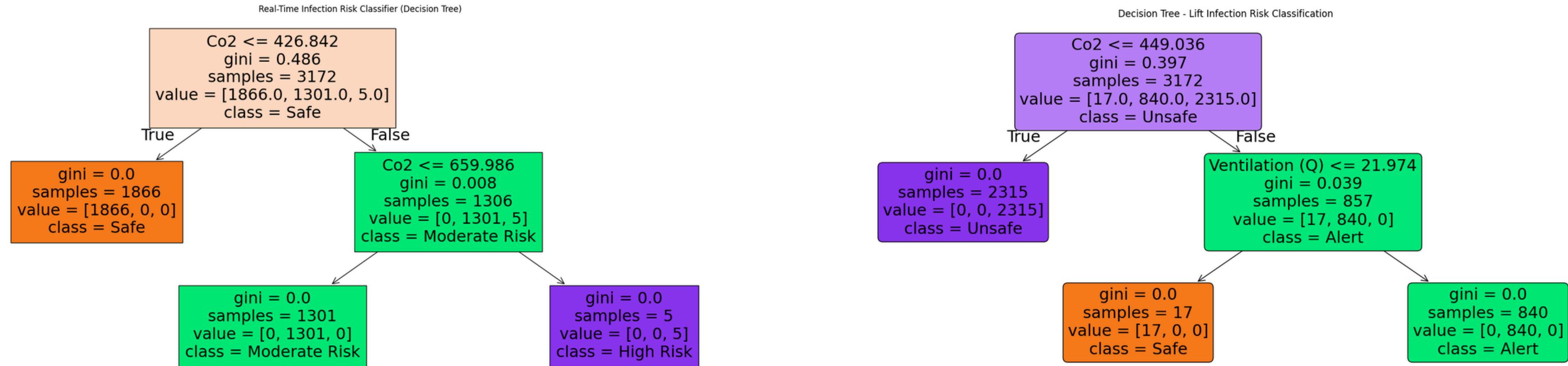
# Profiling Lift Environments Using K-Means Clustering

## Dominant Drivers of Risk

Temperature and CO<sub>2</sub> were found to be the most direct indicators of ventilation quality and occupancy load—key factors in infection risk. Humidity had lower variance and less discriminative power.



# Classifying Lift Conditions: From Sensor Data to Safety Labels



Tree 1: CO<sub>2</sub> - Only Classifier

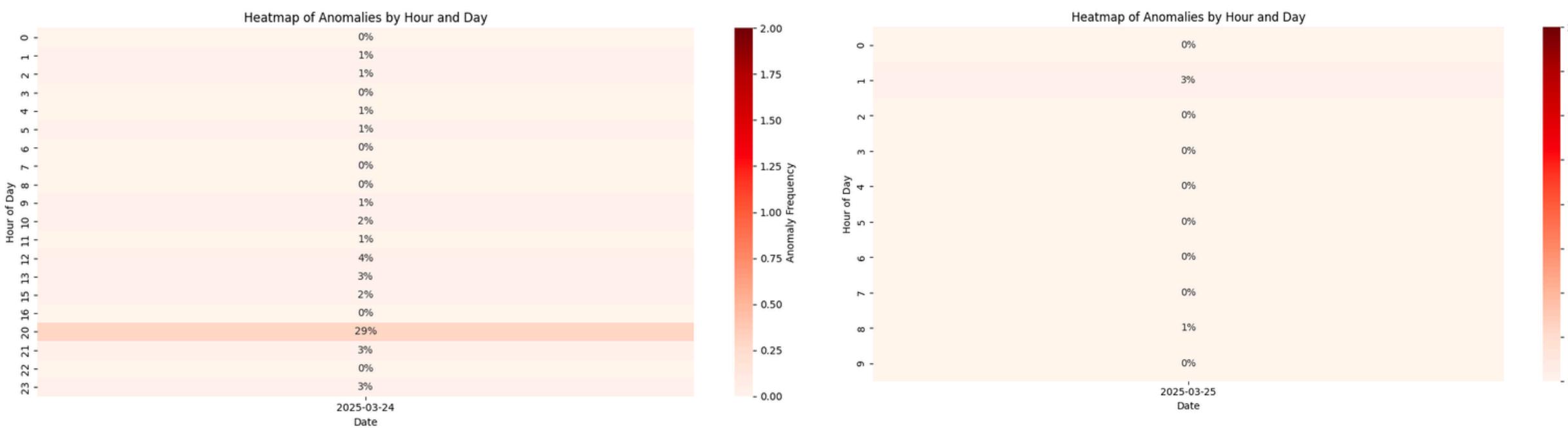
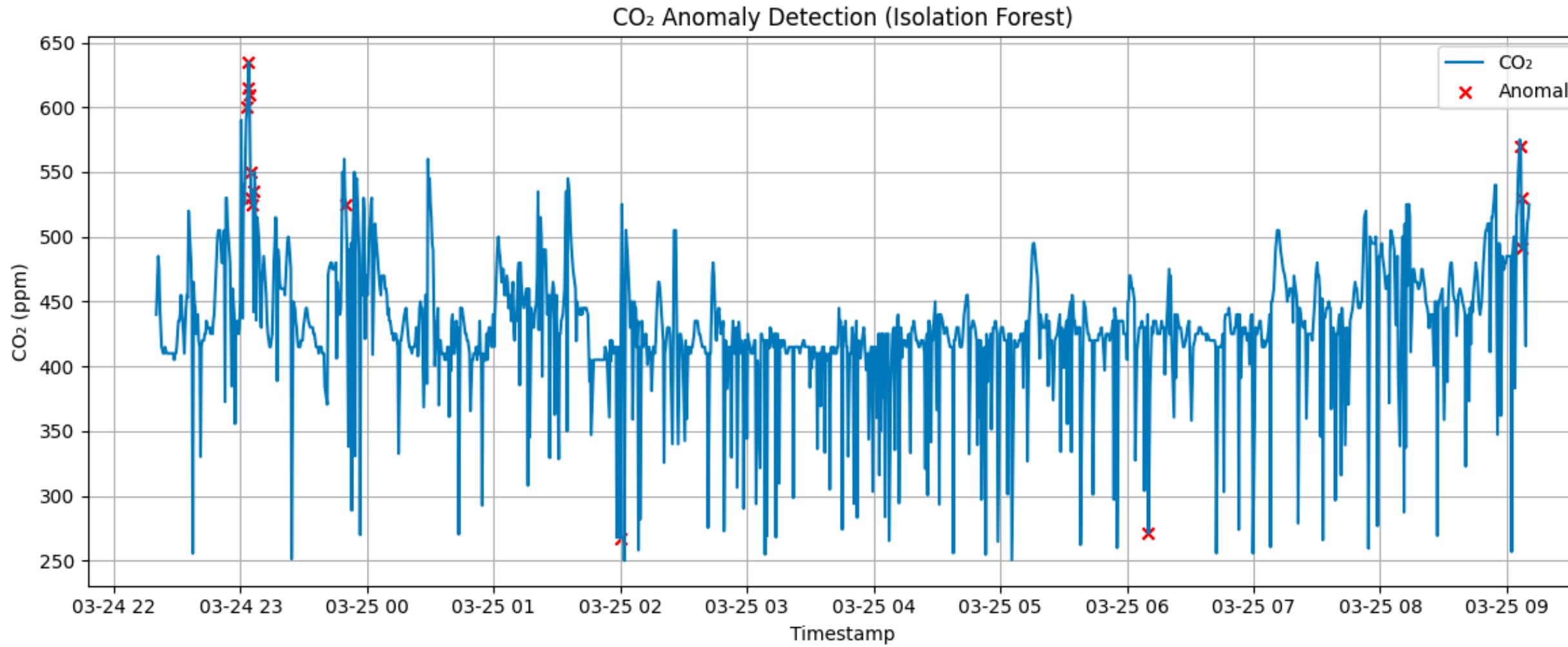
- Risk increases as CO<sub>2</sub> concentration rises.
- Thresholds like 426 ppm and 660 ppm are used to segment risk into safe, moderate, and high.

**Higher CO<sub>2</sub> → higher likelihood of shared air → higher risk.**

Tree 2: Multi-Parameter Risk Classifier

- Low CO<sub>2</sub> doesn't always mean safe – poor ventilation can still allow infectious aerosols to linger.
- The model reveals hidden risk by classifying conditions as unsafe when ventilation (Q) is critically low, even if CO<sub>2</sub> appears acceptable.

# Anomaly Detection: Spotting What Doesn't Belong



Flag anomalies like:

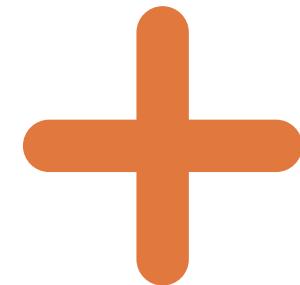
- Sensor Dropout
- Unexpected CO<sub>2</sub> surges
- Ventilation failure

**14 total anomalies were found.**

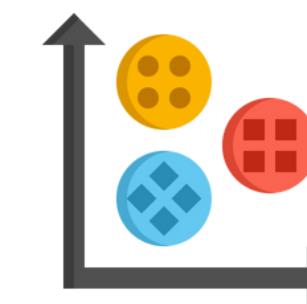
# Bringing It All Together: Real-Time Analytics at the Edge



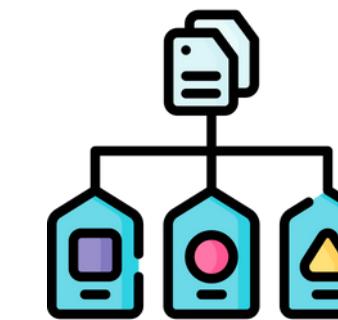
Sensor Data



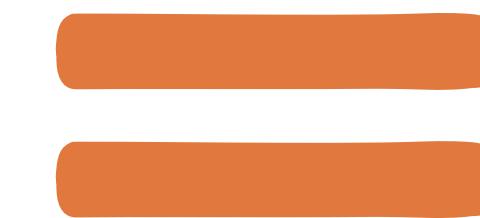
Anomaly Detection



Clustering



Classifier



Labels



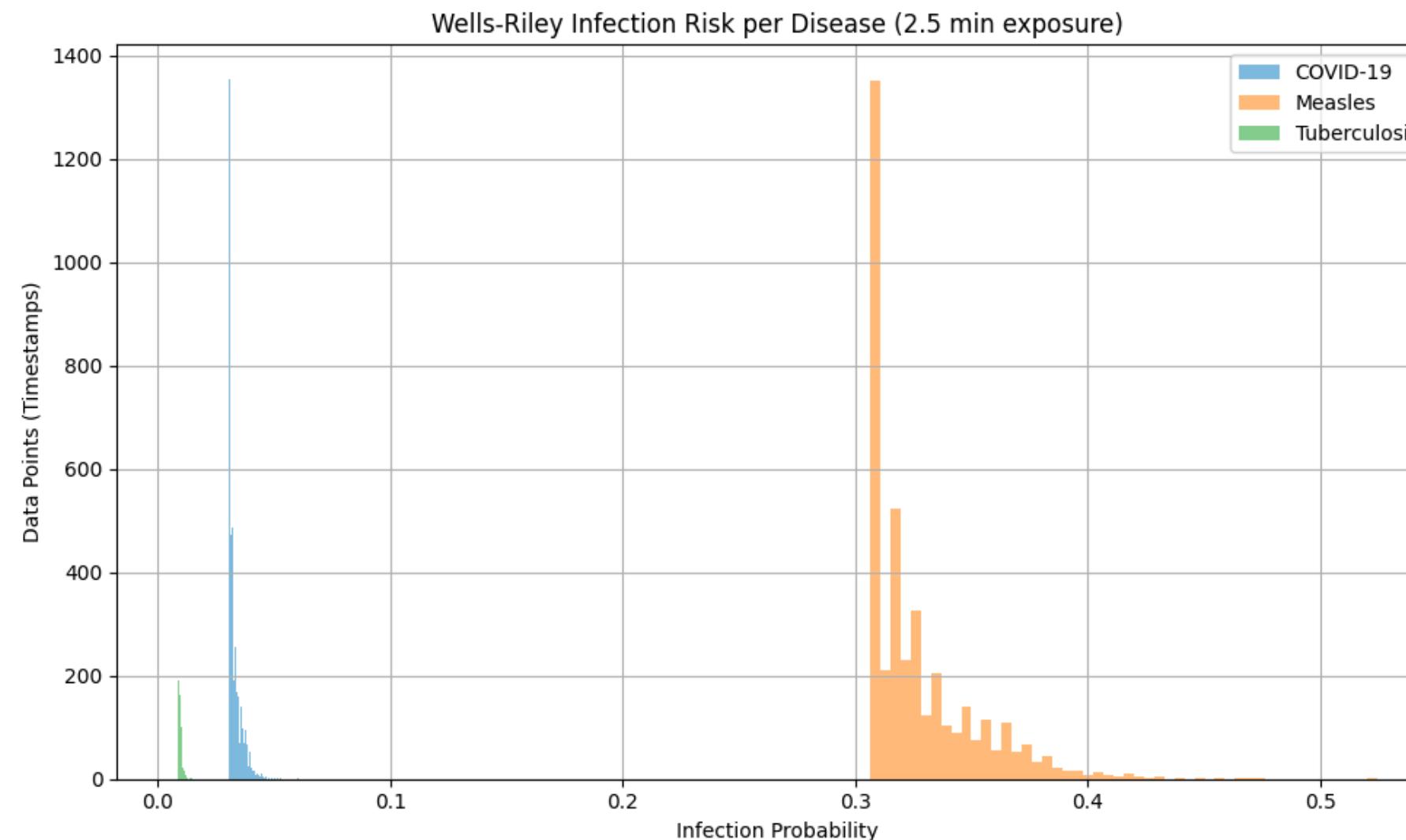
Warnings



Profiles

# Key Results & Insights

# Wells-Riley's Prediction



Covid-19

Infection Rate: 2.38%  
Moderate transmission

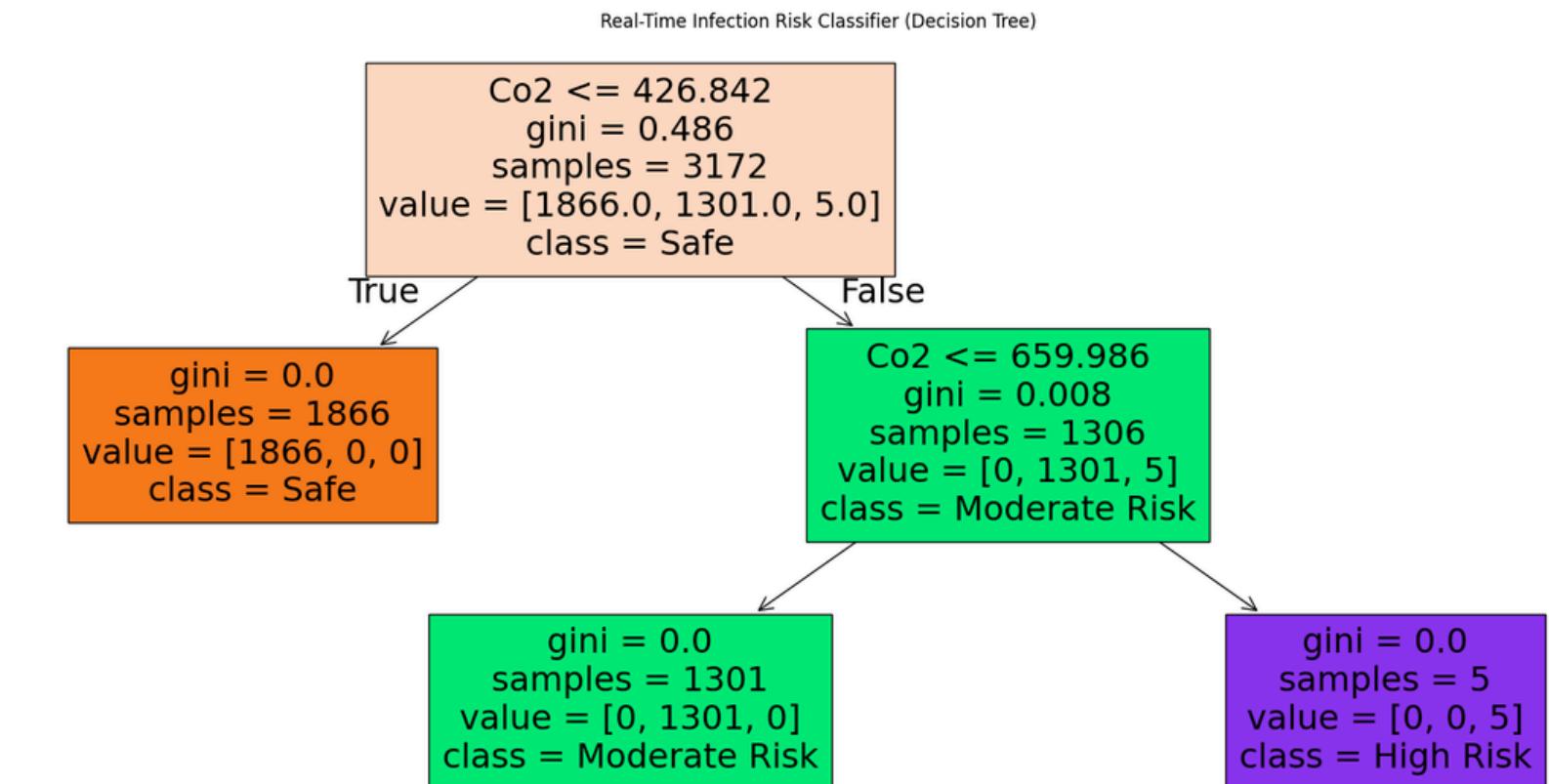
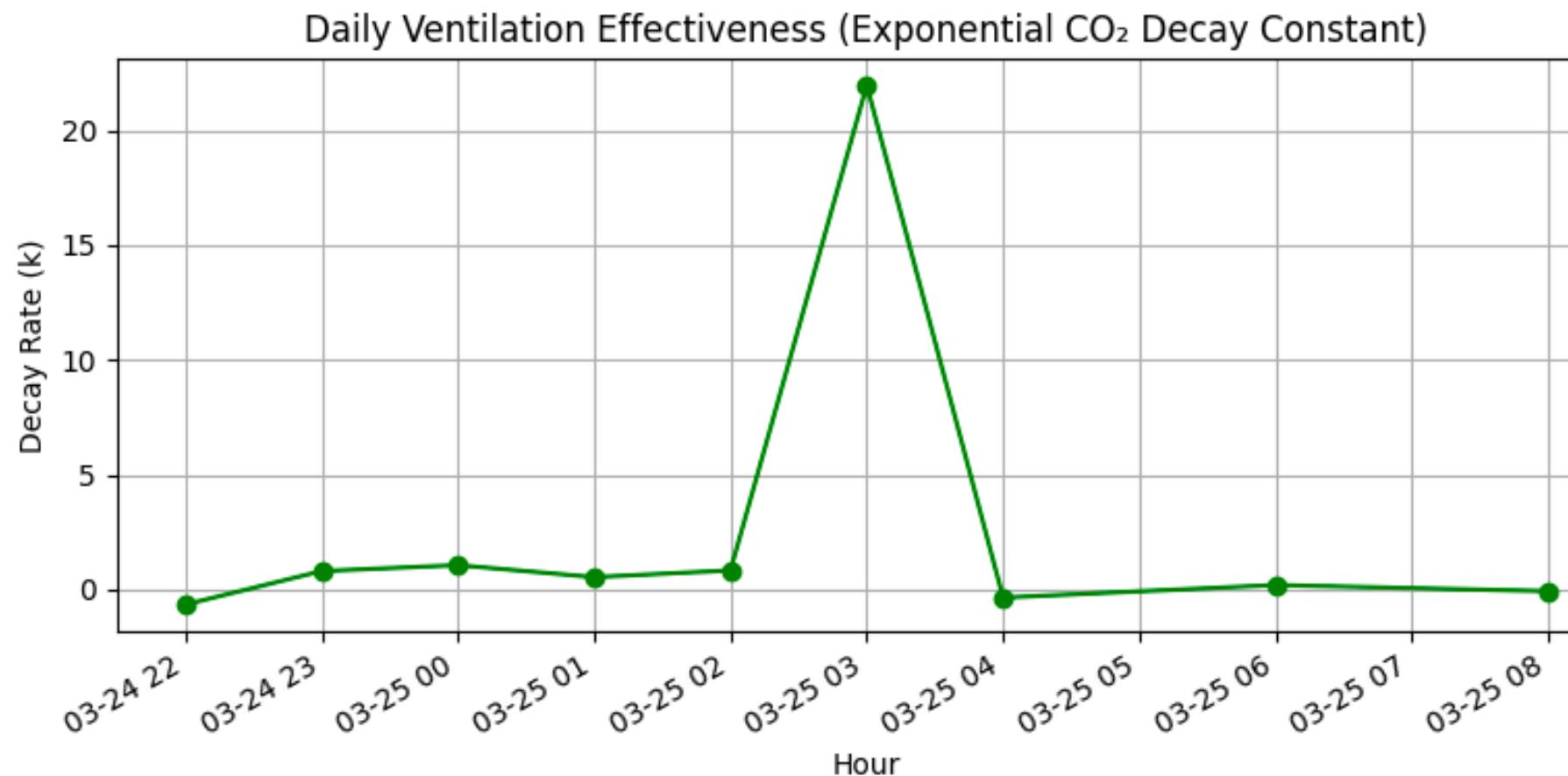
Meales

Infection Rate: 32.68%  
Extremely high risk

TB

Infection Rate: 0.90%  
Lower airborne quanta

# What the Twin Revealed: Risk Hidden in Plain Sight



## Ventilation Reality Check

- CO<sub>2</sub> decay constants near zero in most sessions
- Air wasn't being exchanged, indicating poor ventilation even if conditions felt "normal"

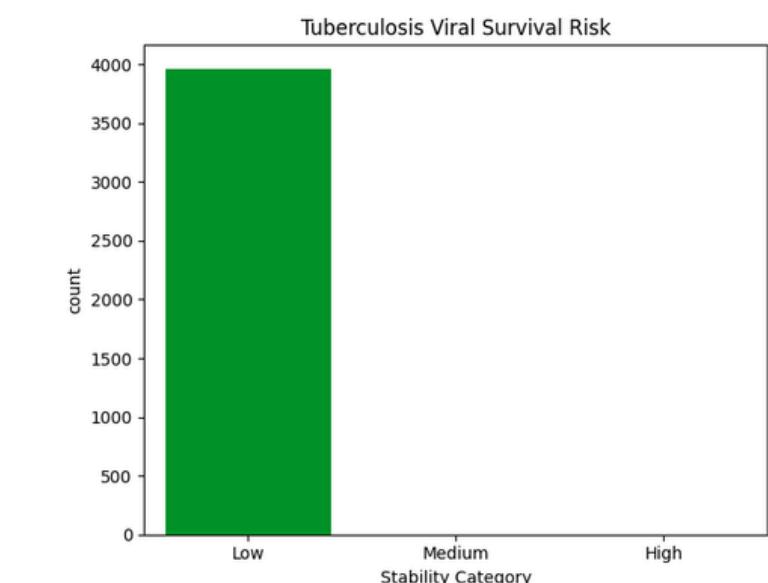
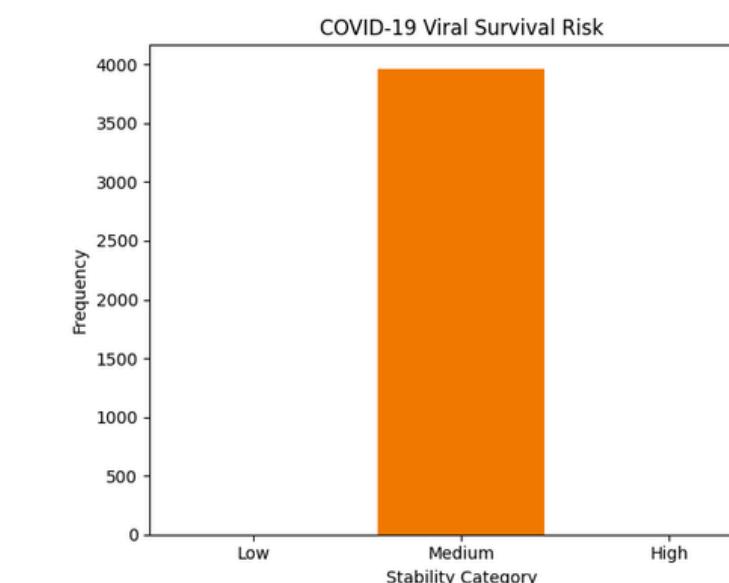
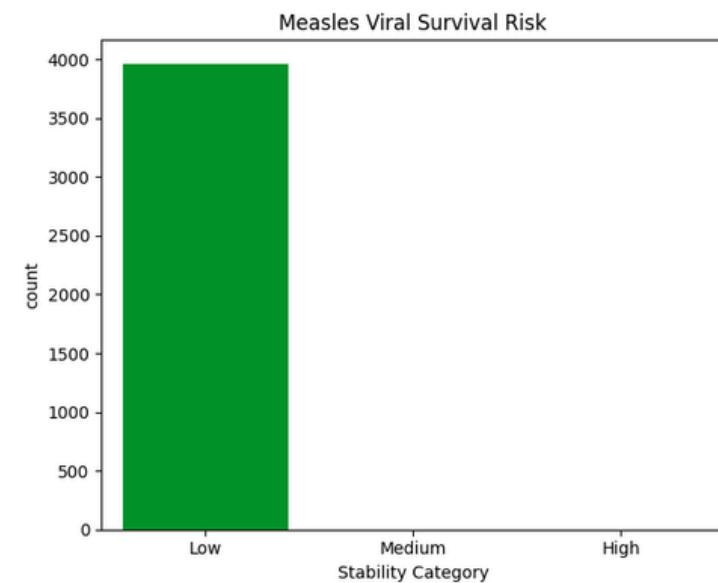
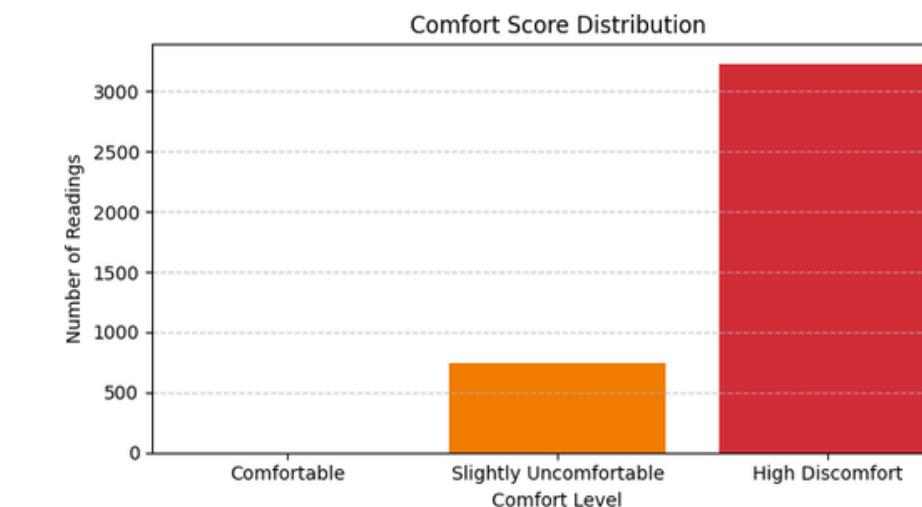
## CO<sub>2</sub> Threshold Logic

- When CO<sub>2</sub> > 660 ppm, risk sharply increases
- This threshold aligned with anomaly spikes and infection probability

# What the Twin Revealed: Risk Hidden in Plain Sight

## Insights: VESS & Comfort Score

- **Measles & TB → Low VESS:** Warm, humid lift conditions limited virus survival for both pathogens.
- **COVID-19 → Medium VESS:** Environmental conditions allowed moderate persistence—still a concern for transmission.
- **High Discomfort Dominates:** Over 80% of readings were "Slightly or Highly Uncomfortable", highlighting thermal stress and its impact on lift usability.
- **Inverse Relationship:** Conditions that reduced virus viability (high humidity) also led to poor thermal comfort—a tradeoff between health risk and occupant experience.



# Conclusion & Future Works

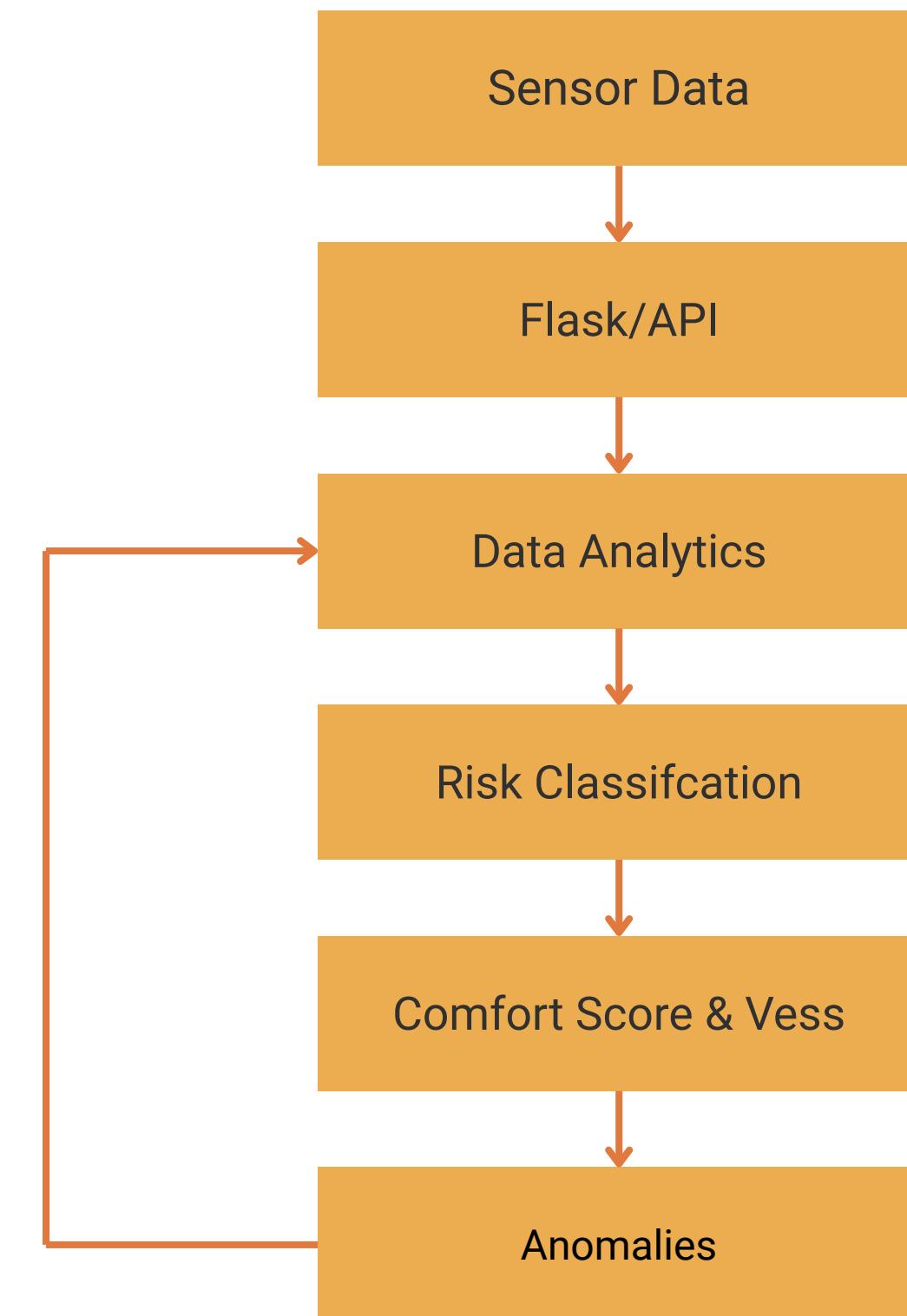
# Digital Twins for Safer Shared Spaces

## Keywords

- A real-time, disease-aware digital twin was successfully built and tested for lifts.
- The system is low-cost, interpretable, and easy to scale to other enclosed environments.
- Combines epidemiological modelling + real-time sensing + ML analytics for layered risk insights.

## Next Step

1. Add occupancy counters for density-aware risk estimation.
2. Develop real-time dashboards for live monitoring and alerts.
3. Expand to other spaces like restrooms, dormitories, and clinics.



# Thank You