CAM: The Iron Dome of Public Health Security in EAC Aviation

11TH AFRICA REGIONAL CAPSCA MEETING - NAIROBI

Dr. Mkwizu


"The most effective way to manage a public health outbreak is to anticipate it — and prepare before it arrives"
Infectious Disease Cases
Infection Rate
COVID 19
Disease Trends
Infection Rate (%)
0
16
20
30

OUTLINE

- Air Travel Seeding Outbreaks
- Pitfalls of Screening
- Airport Surveillance
- Mathematical Models
- AI Models

EAC Partner States

EAC - CASSOA
Centre for Aviation Medicine

Disease	Origin (Year)	Destination
Influenza H1N1	Mexico (2009) [48]	Pandemic [50]
Vibrio cholerae	South Asia (2002, 2008)	Haiti epidemic (2010) [117]
NDM-1 carbapenem-resistant Gram-negative bacteria	India (2009) [84]	Australia, Austria, Belgium, Canada, China, Croatia, Czech Republic, Denmark, France, Germany, Ireland, Italy, Japan, Kuwait, Lebanon, The Netherlands, New Zealand, Norway Oman, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Turkey, United Kingdom, USA [85]
mcr-1 colistin-resistant Gram-negative bacteria	China (2014) [118]	Algeria, Argentina, Belgium, Brazil, Cambodia, Canada, China, Denmark, Egypt, France, Germany, Great Britain, Italy, Japan, Laos, Lithuania, Malaysia, The Netherlands, Nigeria, Poland, Portugal, South Africa, Spain, Switzerland, Taiwan, Thailand, Tunisia, USA, Vietnam [87]
Dengue virus	Primarily Southeast Asia (1950s) [55]	Global emergence over the past five decades [55]

HOW AIR TRAVEL SEEDS OUTBREAKS WORLDWIDE

- Air travel has **introduced or accelerated major outbreaks worldwide.**
- **Single** travelers have sparked **epidemics in distant regions**.
- **Infections** and **resistant bacteria** spread globally **within days** via passengers.
- **Arboviruses like dengue** became globally established through **repeated importations**.

(Findlater & Bogoch, 2018)

MERS-CoV	Saudi Arabia (2012) [25]	Epidemics in South Korea and Saudi Arabia, with cases detected in Algeria, Austria, China, Egypt, France, Germany, Greece, Iran, Italy, Jordan, Kuwait, Lebanon, The Netherlands, Oman, Philippines, Qatar, Thailand, Tunisia, Turkey, Turkey, United Arab Emirates, United Kingdom, USA, Yemen [119]
Zika virus	Africa and Asia [69]	First detected in Latin America and the Caribbean in 2015 with ongoing transmission in the South Pacific, Latin America and the Caribbean [71]
Chikungunya virus	Asia and Africa [8,121]	Latin America and the Caribbean in December 2013 with ongoing transmission in this region [120], and autochthonous cases in Europe [60]
SARS-CoV (2002)	Southern China (2002) [22]	Epidemics in Hong Kong, Canada, USA, Vietnam, Singapore, Philippines, and Mongolia [22]
Schistosomiasis	Africa	Epidemic in Corsica (2013), with ongoing transmission [20]

(Findlater & Bogoch, 2018)

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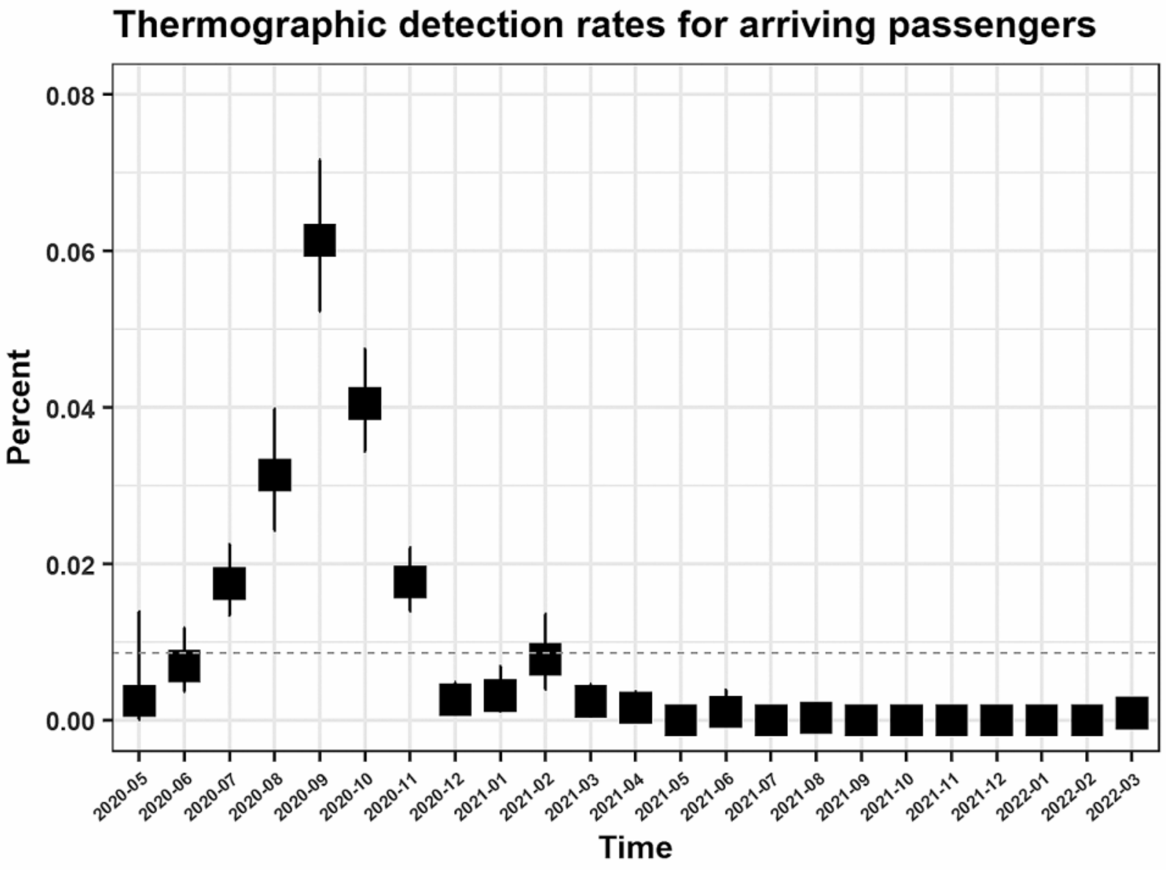
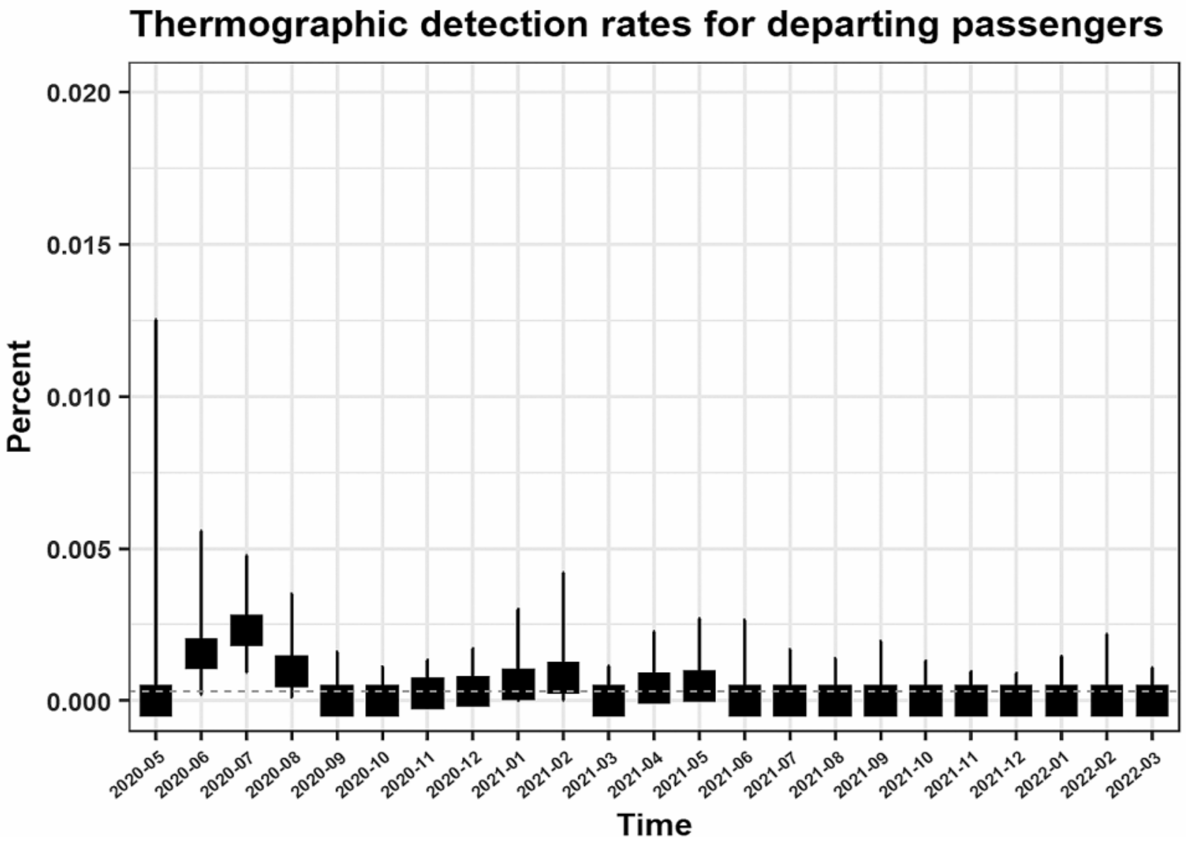
MODELLING EVIDENCE ON AIRPORT SCREENING

- **Screening misses many cases**
- **Asymptomatic spread** is a major gap
- **Continuous surveillance** needed
- **Predictive modelling essential**
- **Travel restrictions only delay spread**

Study	Type of restrictions and setting	Study design	Viral strain involved	Strain transmissibility (R0)	Scenario and duration of intervention	Effect estimate
Quilty *et al.*, 2020[15]	Effectiveness of exit and entry screening for detecting travellers entering Europe with COVID-19 infection	Mathematical stochastic model	SARS-CoV-2	Not reported	Assume 100 infected air travellers who in the absence of screening would arrive at their destination infected Of 100 travellers, how many are likely to:	
					• be detected via exit screening on departure	44% (95% CI 33 - 56)
					• present with severe disease during travel	0% (95% CI 0 - 3)
					• be detected via entry screening on arrival	9% (95% CI 2 - 16)
					• not be detected	46% (95% CI 36 - 58)
Mandal *et al.*, 2020[21]	Port-of-entry symptom screening of travellers with clinical features and from COVID-19-affected countries; India	Deterministic model and stochastic models	SARS-CoV-2	R0=1.5	Infectiousness of asymptomatic cases relative to symptomatic cases = 0	Cumulative incidence reduction of COVID-19 infection = 62%
				R0=4	Infectiousness of asymptomatic cases relative to symptomatic cases = 0.5	Cumulative incidence reduction of COVID-19 infection = 2%
Gostic *et al.*, 2020[20]	Travel screening (exit screening only, entry screening only or a combination of both)	Probabilistic model	SARS-CoV-2	R0=1.5 - 3.5	Exit screening only (5% subclinical)	Fraction detected = 0.21
					Entry screening only (5% subclinical)	Fraction detected = 0.27
					Combination of exit and entry screening (5% subclinical)	Fraction detected = 0.34
Chinazzi *et al.*, 2020[22]	Domestic and international travel restrictions from China	Individual-based stochastic and spatial epidemiological models (meta-population approach)	SARS-CoV-2	R0=2.4	Local travel quarantine within China	Local epidemic in China: travel quarantine reduces the overall epidemic progression by only 3 - 5 days
				R0=2.4	International travel quarantine	International scale: travel quarantine reduces the number of case importations by 80%

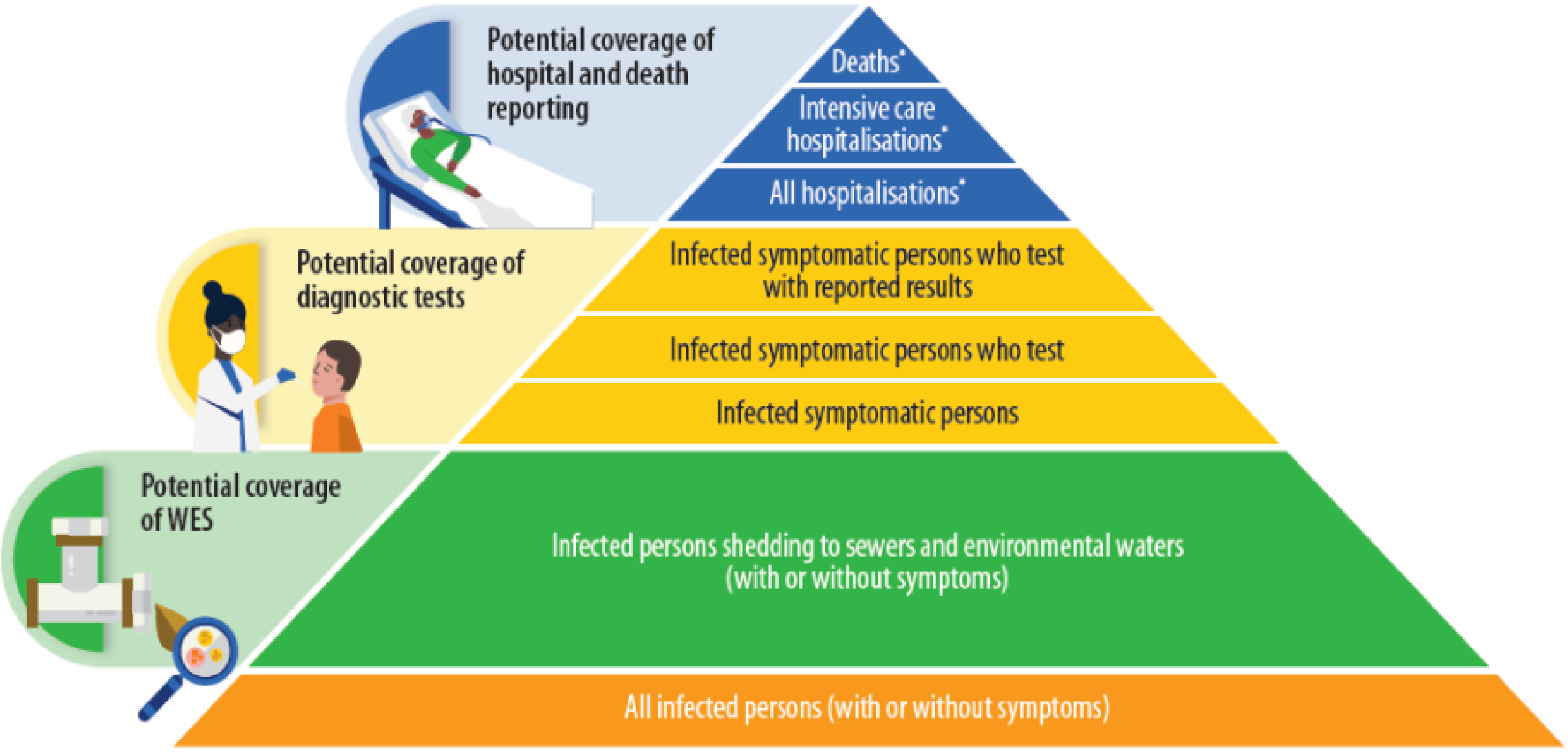
(Chetty et al., 2020)





- Thermography detected **almost no cases**.
- **Peaks** did not reflect real COVID-19 trends.
- **Departures** showed **near-zero detections**.
- **Non-symptom-based** surveillance is needed.

(Takayama et al., 2024)



Wastewater Surveillance Covers the Whole Infection Pyramid

(ECDC, 2024)

- **Wastewater Surveillance (WES)** detects **all infected people**, including **asymptomatic and untested.**
- Diagnostic tests capture only **symptomatic testers.**
- Hospital data reflects **only severe cases**.
- WES provides the **broadest coverage and strongest early-warning signal.**

EVOLUTION OF AIRPORT-BASED SURVEILLANCE

Milestones	2021 Sep 29–Nov 27	2021 Nov 28–Dec 31	2022	2023	Jan–Aug 2024
Launch	Launched 6-week pilot, demonstrating operational feasibility and detection and genomic sequencing of SARS-CoV-2 in samples from travelers	Expanded pilot for Omicron surge; identified Omicron subvariants BA.2 and BA.3 six weeks before those variants were reported globally (*2*)	Launched airplane wastewater pilot at JFK (*5*); demonstrated retroactively that US predeparture test requirement during COVID-19 pandemic reduced postarrival positivity by 50% (*8*); enhanced surveillance for 2022 FIFA World Cup (*9*)	Expanded coverage of flights from China and surrounding hubs during China's removal of its "zero-COVID" policy and subsequent surge of cases; detected first BA.2.86 in a traveler from Japan (*10*); detected FLiRT† mutations in wastewater samples 3 weeks before reported globally	Launched transatlantic airplane wastewater pilot in collaboration with United Kingdom Health Security Agency; enhanced surveillance during Hajj and 2024 Summer Olympics
Airports involved	EWR, JFK T4, SFO	ATL, EWR, JFK T4, SFO	ATL, EWR, IAD, JFK T4, SFO	ATL, BOS, EWR, IAD, JFK T4, JFK T8, LAX, SEA, SFO	BOS, EWR, IAD, JFK T4, JFK T8, LAX, MIA, SEA, SFO
Modalities	Nasal sampling in airport; at-home saliva sampling with questionnaire	Nasal sampling in airport; at-home saliva sampling with questionnaire	Nasal sampling in airport and traveler questionnaire; discontinued at-home saliva sampling; airplane wastewater sampling	Nasal sampling in airport and traveler questionnaire; airplane wastewater sampling; airport triturator;‡ air monitoring	Nasal sampling in airport and traveler questionnaire; airplane wastewater sampling; airport triturator; air monitoring
Median (range) participants per week§	535 (19–1395)	1,434 (1,334–1,746)	1,217 (325–3,490)	6,320 (1,689–9,321)	7,249 (4,366–12,628)
Median (range) traveler countries of origin per week§	1	6	43 (6–87)	123 (56–138)	143 (116–161)
Wastewater samples collected	0	0	89	417	783
Air samples collected	0	0	0	93	438
Laboratory methods used	RT-PCR, amplicon-based sequencing	RT-PCR, amplicon-based sequencing	RT-PCR, amplicon-based sequencing, target enrichment sequencing	RT-PCR, dRT-PCR, amplicon-based sequencing, target enrichment sequencing	RT-PCR, dRT-PCR, amplicon-based sequencing, target enrichment sequencing
Pathogen targets	SARS-CoV-2	SARS-CoV-2	SARS-CoV-2, influenza A and B pilot	SARS-CoV-2, influenza A and B, RSV testing of nasal samples, air, and wastewater; *Mycoplasma pneumoniae* testing of nasal samples in response to global outbreak reports; mpox testing of airplane and triturator‡ wastewater	Expanded multipathogen enrichment sequencing panel for up to 66 viruses deployed for wastewater samples

- **Early variant detection** is achievable
- Combine **nasal, wastewater, and air sampling** for stronger surveillance
- **Wastewater** offers a **fast, low-cost early-warning signal**
- **Multi-pathogen testing** improves future outbreak preparedness

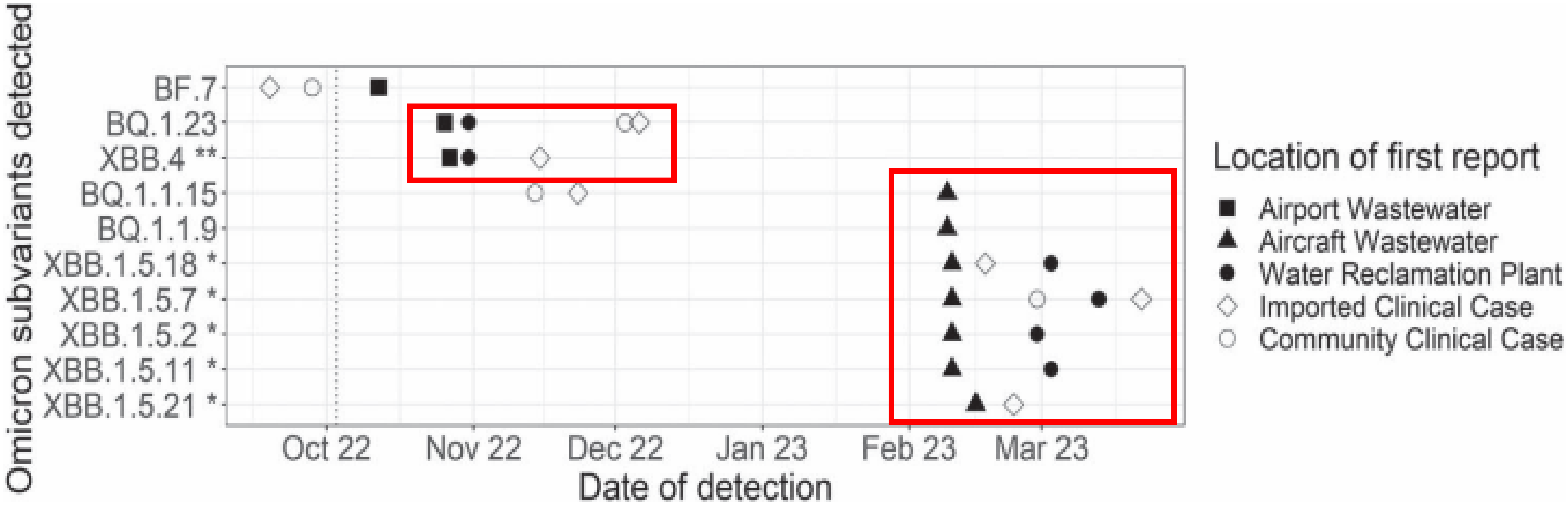
(Friedman et al., 2025)

		Mid-Haul Flights (n=7)	Long-Haul Flights (n=5)	Airport Terminal (n=12)
	Start Date:	8 Jan	6 Feb	9 Jan
	End Date:	23 Jan	23 Feb	23 Feb
Respiratory	Coronavirus 229E			5 (42%)
Respiratory	Coronavirus HKU1			6 (50%)
Respiratory	Coronavirus NL63	1 (14%)		3 (25%)
Respiratory	Coronavirus OC43			8 (67%)
Respiratory	Human Metapneumovirus			
Respiratory	Human Rhinovirus/Enterovirus	2 (29%)	3 (60%)	10 (83%)
Respiratory	Influenza A	1 (14%)		7 (58%)
Respiratory	Influenza B			2 (17%)
Respiratory	Parainfluenza 1			1 (8%)
Respiratory	Parainfluenza 2			1 (8%)
Respiratory	Parainfluenza 3		1 (20%)	7 (58%)
Respiratory	Parainfluenza 4			2 (17%)
Respiratory	RSV	1 (14%)	1 (20%)	
Enteric	Norovirus (GII)	6 (86%)	2 (40%)	12 (100%)
Enteric	Aichivirus	2 (29%)	1 (20%)	11 (92%)
Enteric	Adenovirus	4 (57%)	2 (40%)	11 (92%)
Enteric	Hepatitis A Virus	1 (14%)		

(Tay et al., 2024)

AIRPORT WASTEWATER

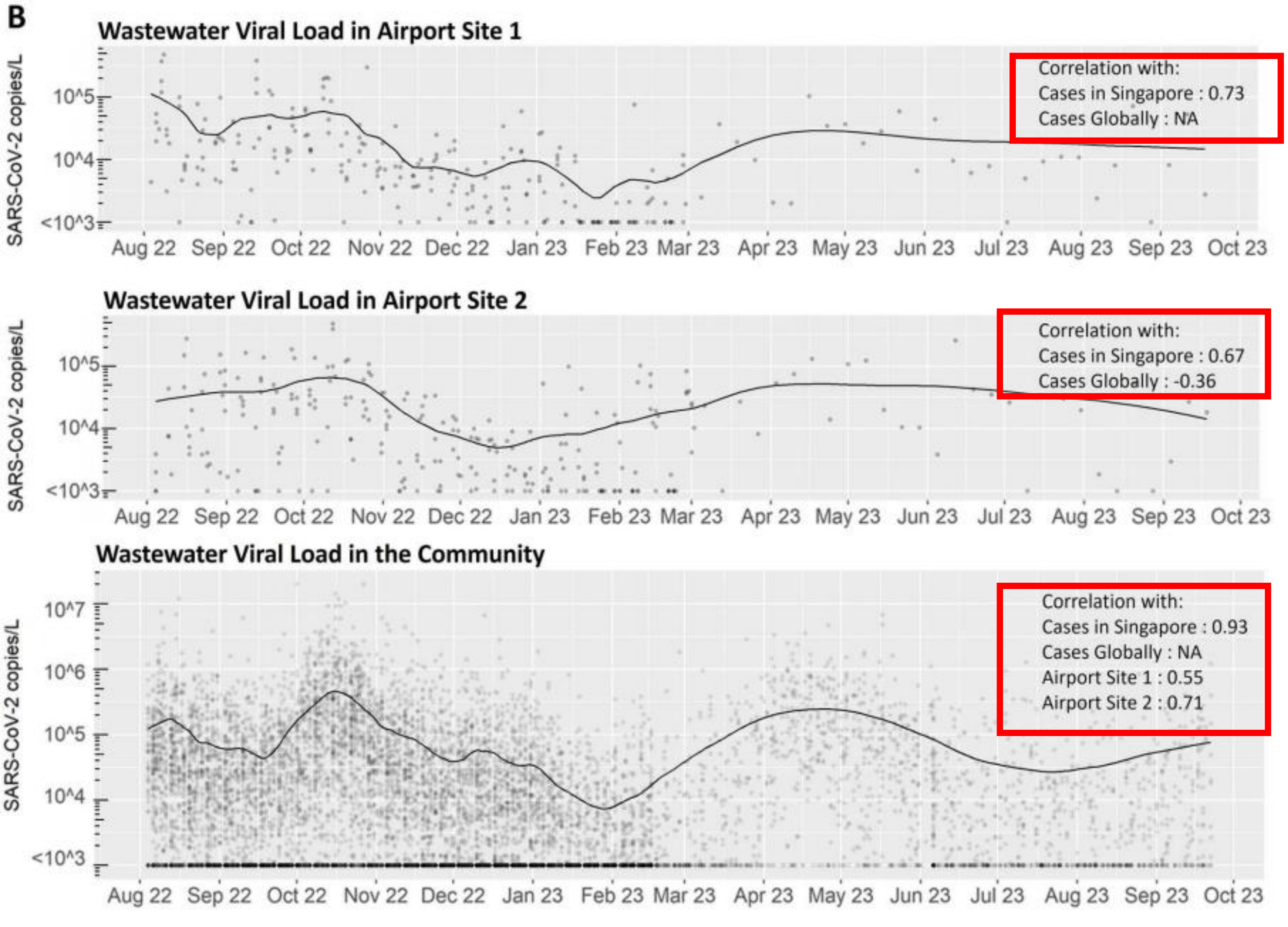
- Airport wastewater had **more pathogens** due to **mixed sewage**.
- Aircraft wastewater still detected key viruses, **especially on long flights.**
- **Enteric viruses** were the **most common.**
- **Wastewater** works **for multi-pathogen surveillance.**
- It provides **early warning for** infectious diseases.



EARLY DETECTION OF VARIANTS THROUGH AIRCRAFT WASTEWATER

(Tay et al., 2024)

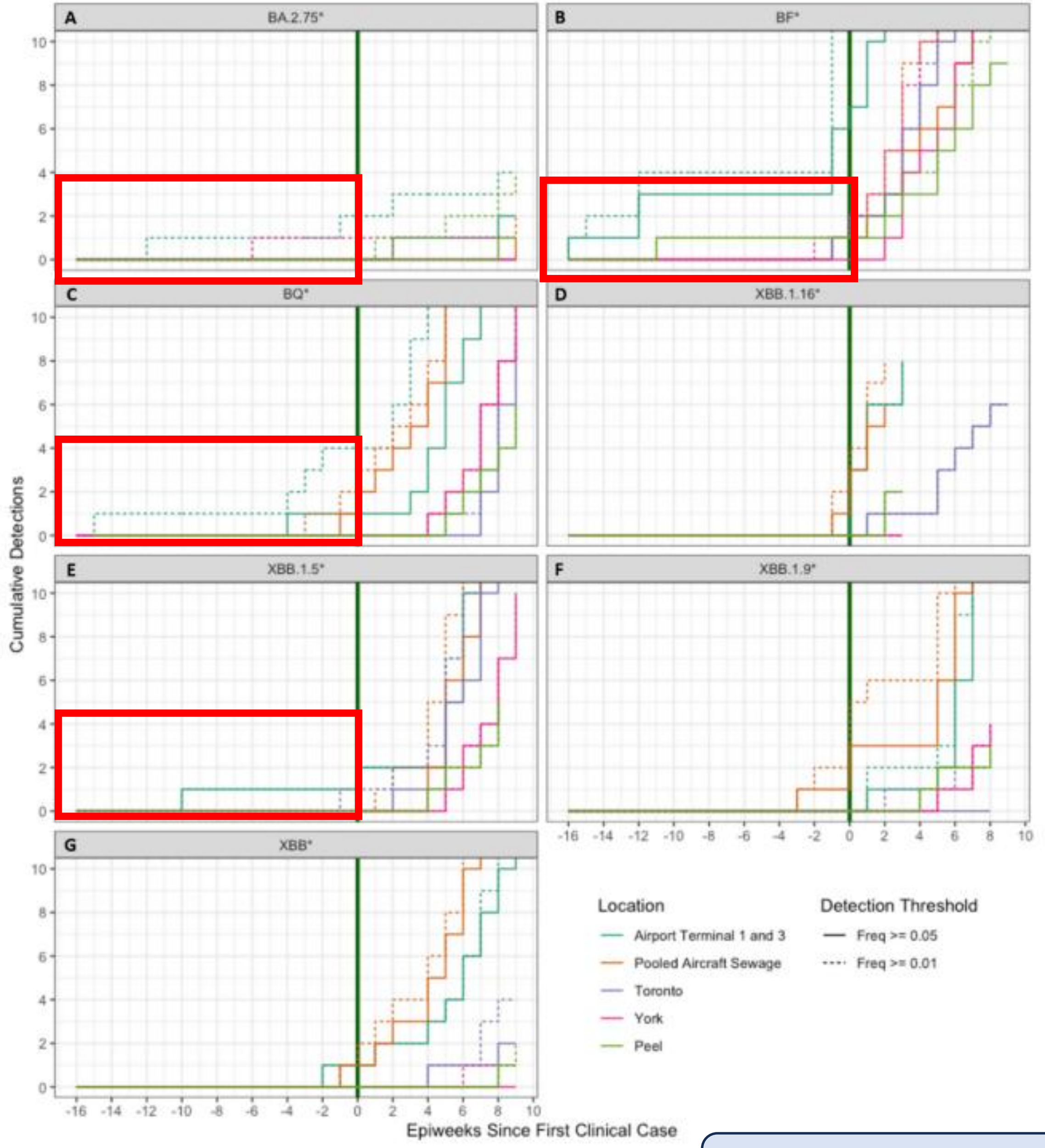
- **Aircraft wastewater** detected variants **earliest.**
- **Airport wastewater** gave **some early signals**.
- **Clinical cases** appeared **weeks later.**
- Wastewater—especially **aircraft sampling—is a strong early warning tool.**



(Tay et al., 2024)

AIRPORT WASTEWATER MIRRORS AND PREDICTS LOCAL COVID-19 TRENDS

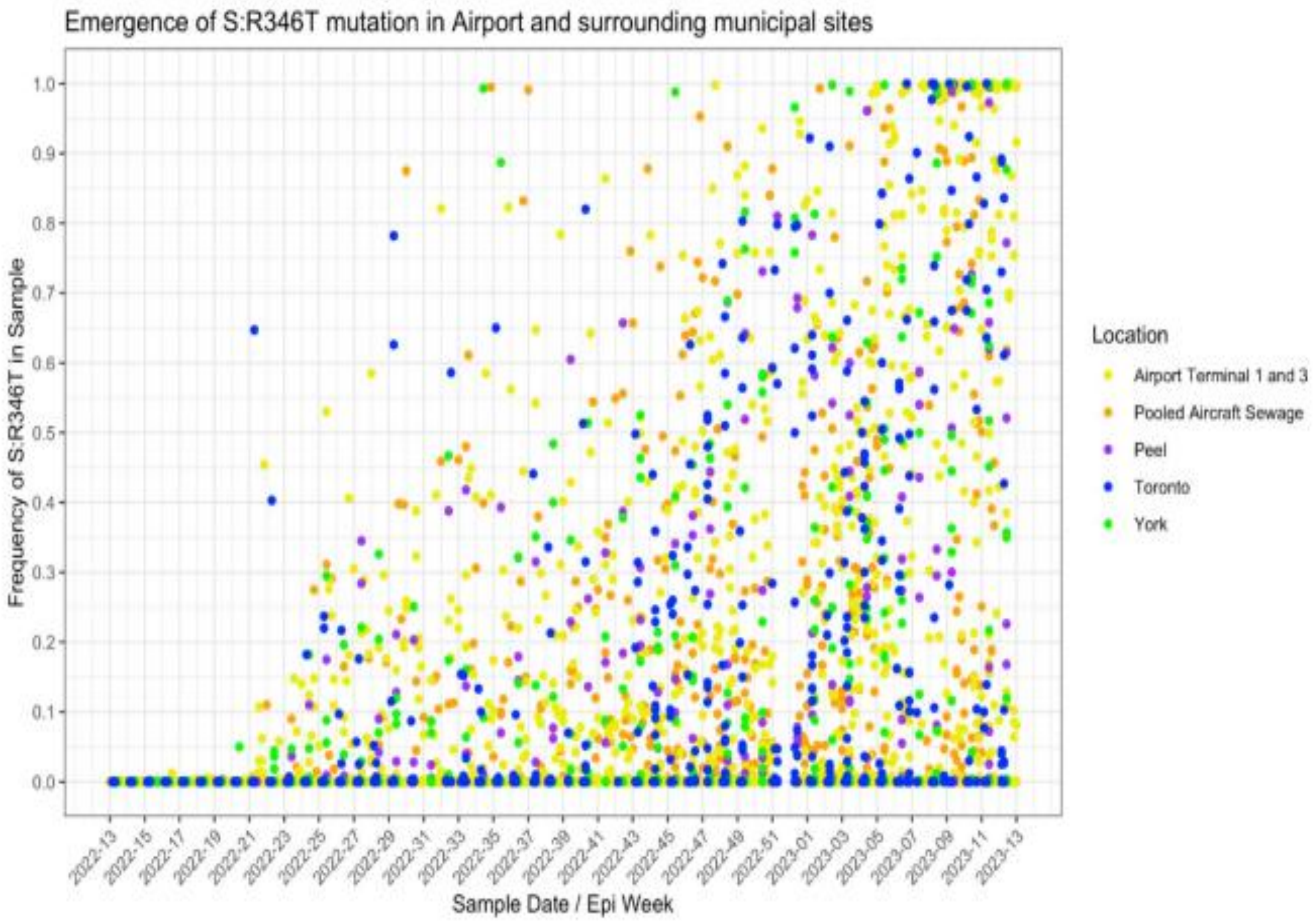
- **Airport** wastewater **closely matches national COVID-19 trends**.
- **Community** wastewater **aligns the strongest with national cases**.
- **No link with global cases**—airport signals reflect **local transmission.**



AIRPORT WASTEWATER = EARLY WARNING

- **Wastewater** at airports detected variants **2-10 weeks before clinical identification**.
- Early signals were visible at <1% frequency, proving high sensitivity.
- **Aircraft sewage** indicated **initial importation events.**

(Overton et al., 2024)

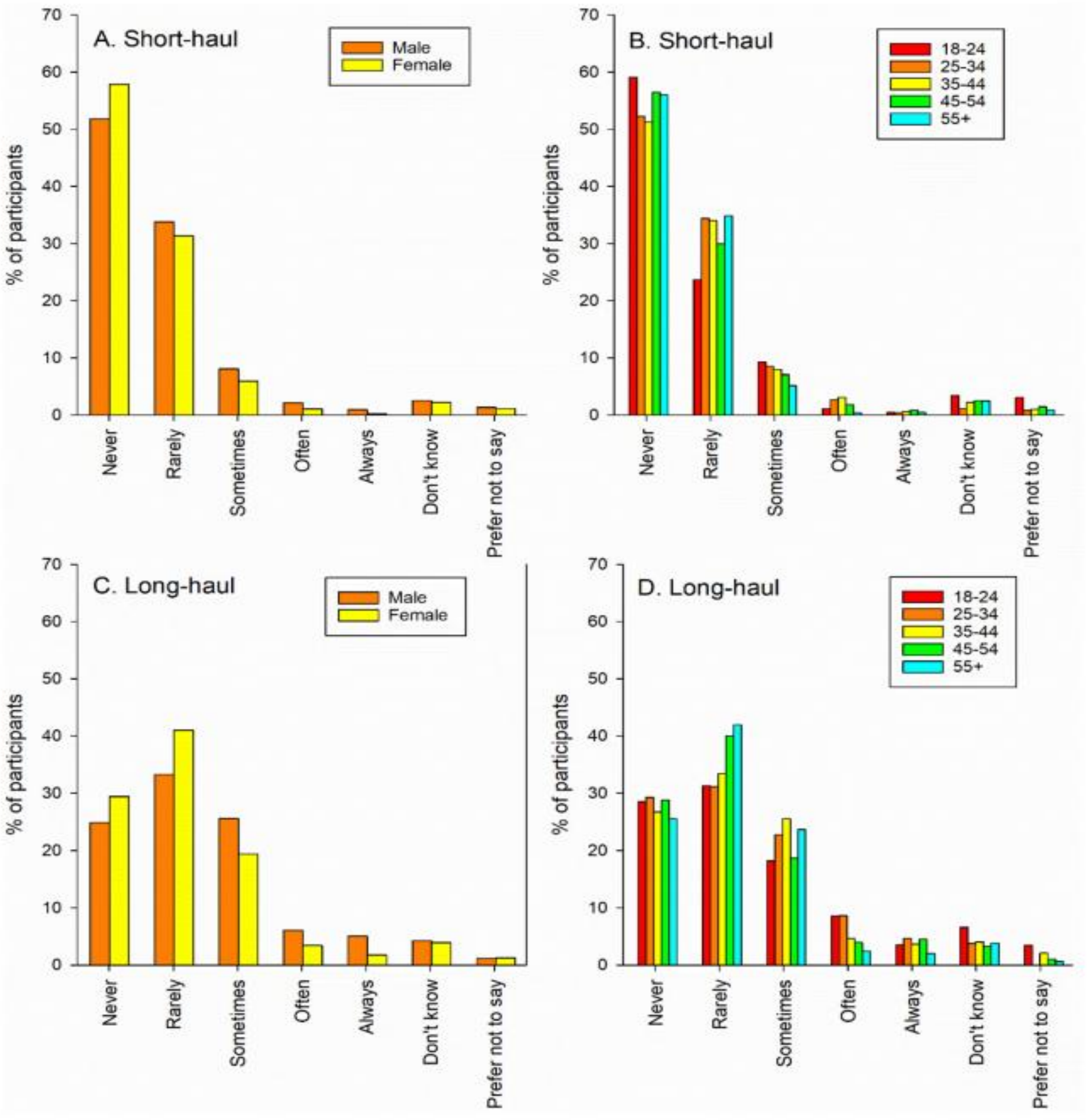


AIRPORT WASTEWATER = EARY WARNING

- Wastewater shows how **key mutations emerge and spread across travelers and** communities.
- Mutation trends reveal **viral evolution and immune-escape pressure.**
- Airport and municipal wastewater together show **how viruses change over time.**

(Overton et al., 2024)

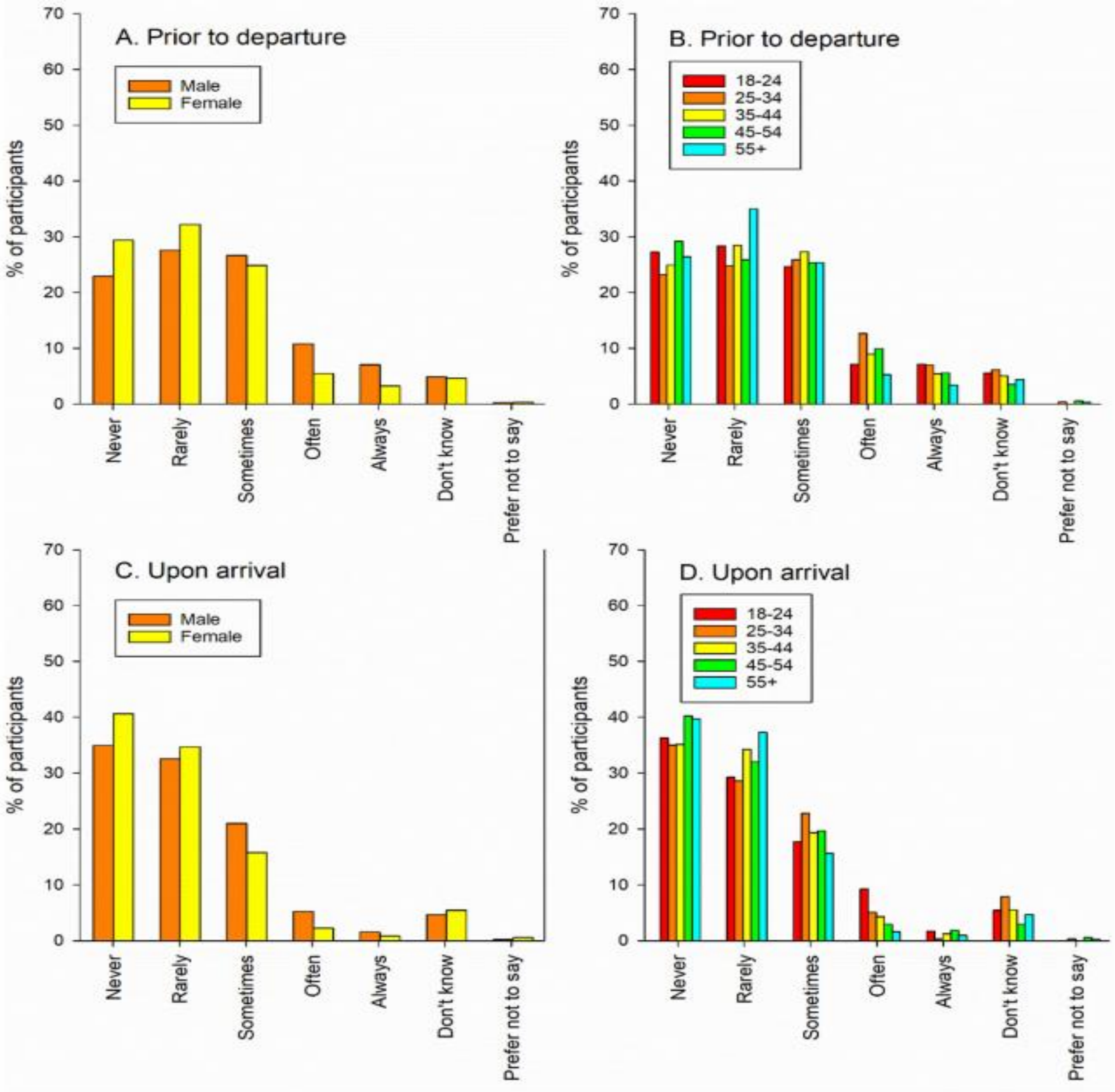
Passenger Toilet Use on Short- and Long-Haul Flights



(Jones et al., 2023)

- **Short-haul flights**: **Very low toilet use** → weak wastewater signals.
- **Long-haul flights**: **Higher toilet use** → better detection potential.
- **Younger passengers** & **males** use toilets more frequently.

Toilet Use Before Departure and Upon Arrival



- **Most passengers defecate before departure**, giving strong wastewater signals.
- **Very few defecate after arrival**, so arrival wastewater is weak.
- **Younger passengers and males** are more **likely to use toilets pre-departure**.

(Jones et al., 2023)

Traveler & Route-based Risk Differences

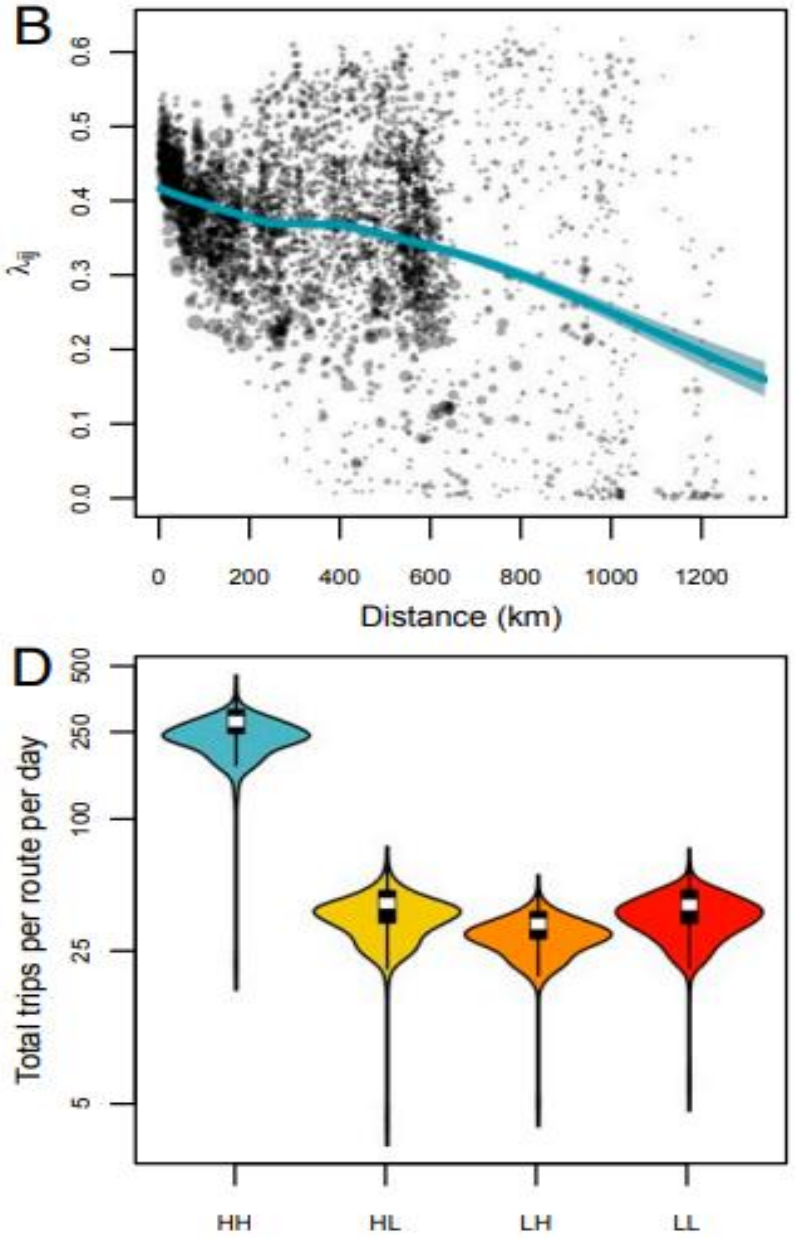
Essential Travelers
- Higher positivity (greater infection probability)
- Lower total impact due to fewer travelers

Non-Essential Travelers
- Lower positivity (screened/tested)
- Main Source of imported cases due to high volume

High Volume Routes
- Large number of passengers increase total importations
- Even low positivity results in high overall risk

High Positivity Routes
- Lower volume but higher infection probability
- Key for early detection of emerging hotspots

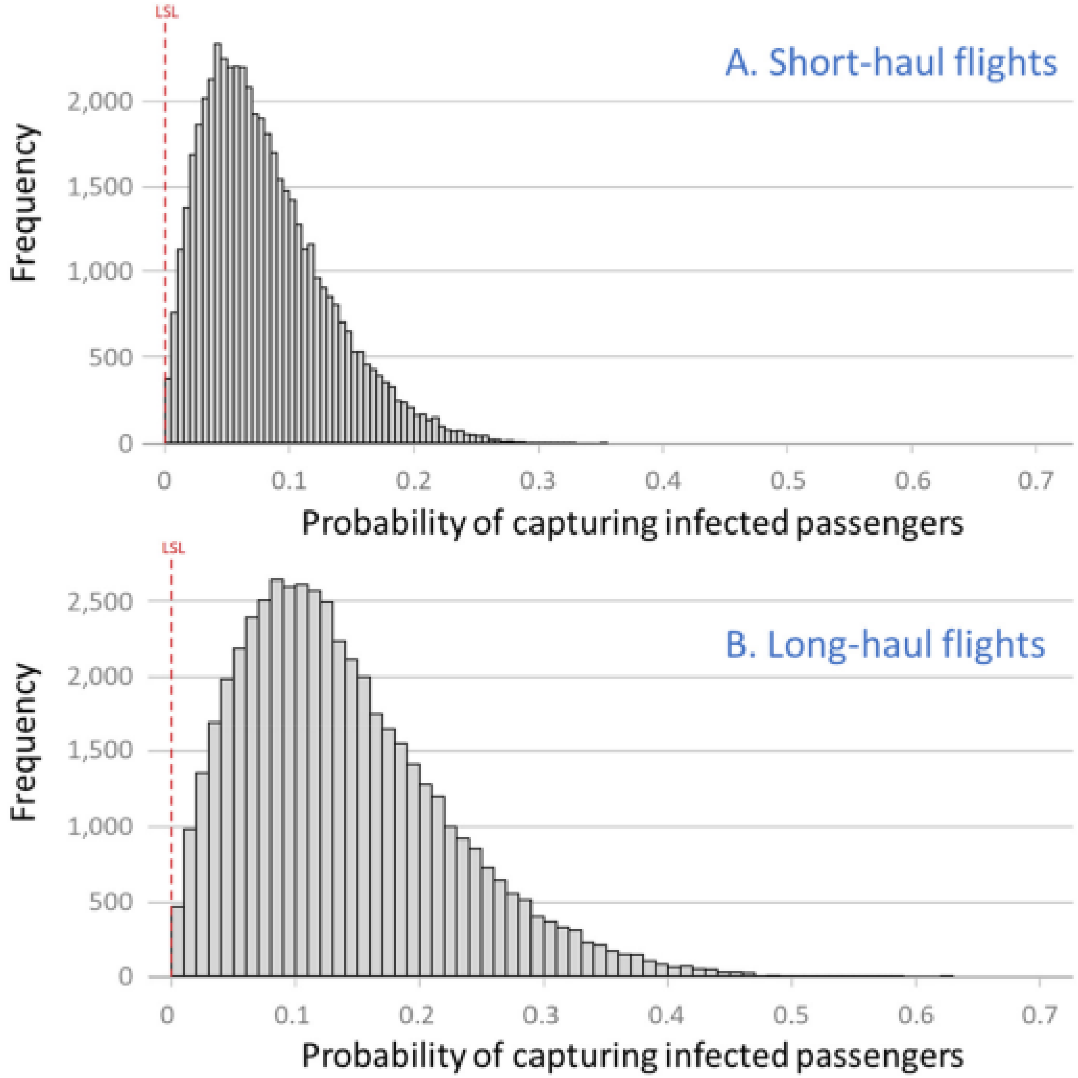
(Milwid et al., 2024)



How Travel Patterns Drive Disease Spread

- **Long trips** mean **longer stays and higher transmission risk**.
- City-to-city routes have the most travellers and **fastest spread.**
- **Frequent short trips** between hubs **move diseases quickly.**
- **Rural routes** get **few travellers** and **slower introductions.**

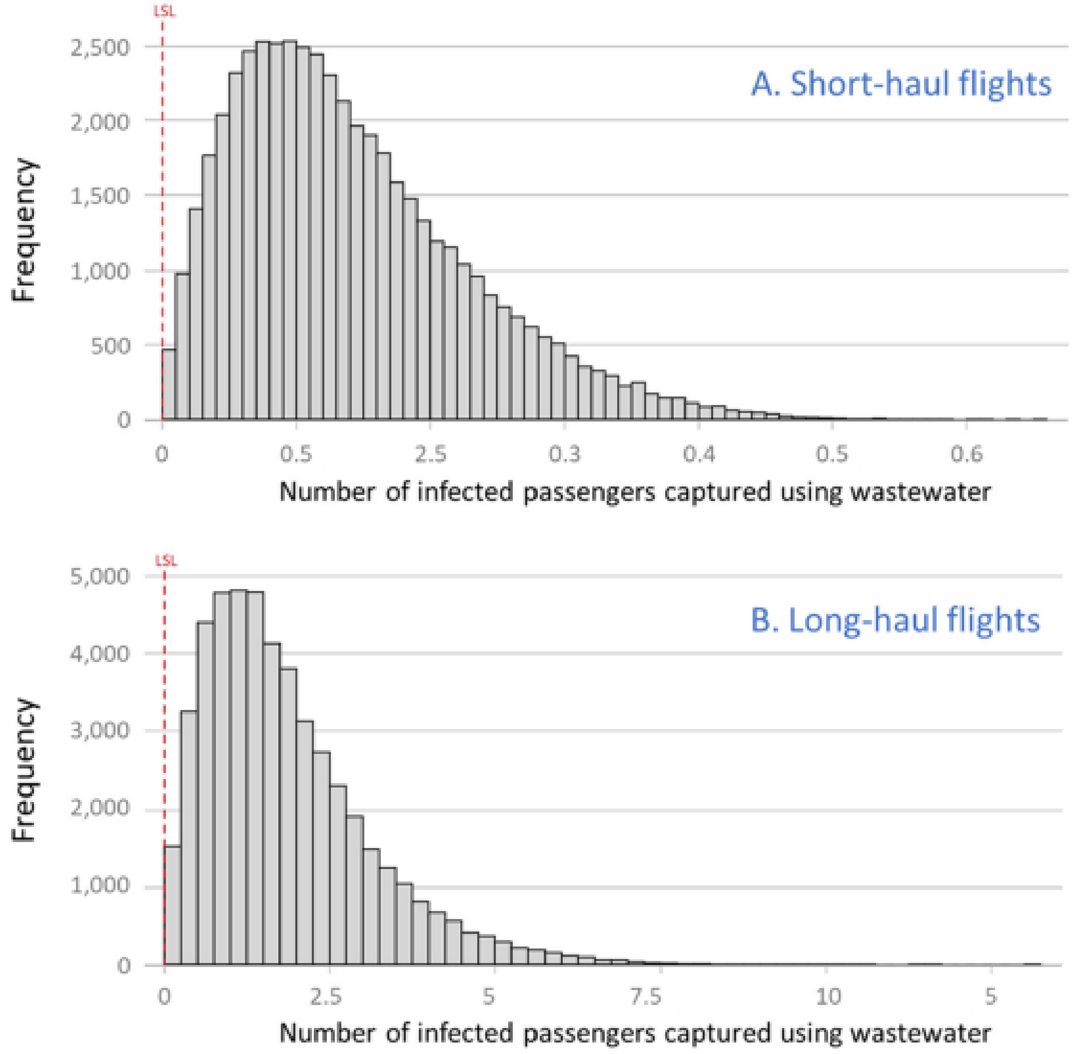
(Giles et al., 2020)



(Jones et al., 2023)

Probability of Detecting Infected Passengers via Wastewater

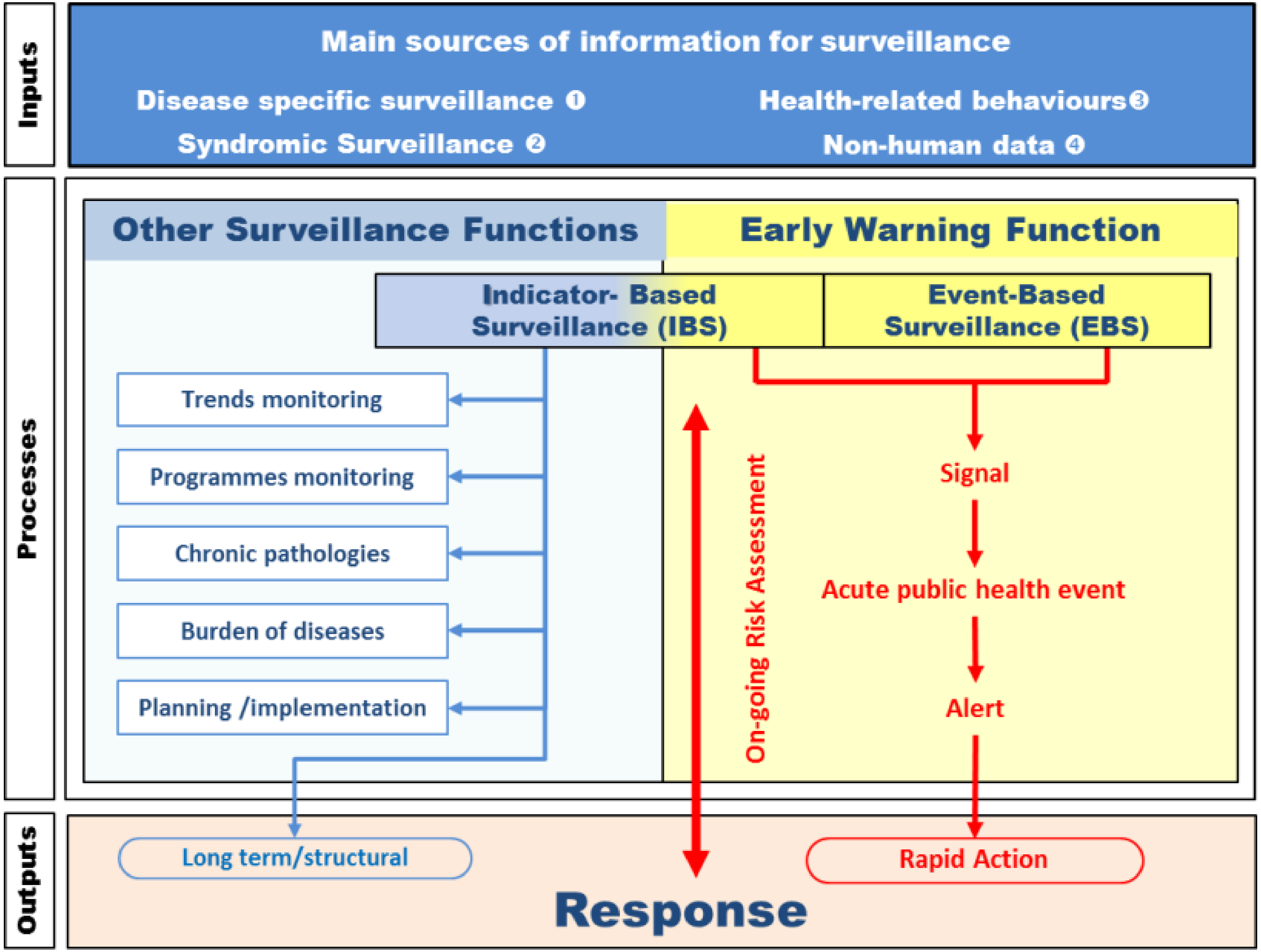
- **Short-haul flights** show very **low detection rates (~5–10%).**
- **Long-haul flights** perform better, with **probabilities around 10–20%.**
- **Aircraft wastewater** captures only a **fraction of infected travelers.**



Number of Infected Passengers Captured via Aircraft Wastewater

- **Short-haul flights** capture **very few infected passengers**, often **below one per flight.**
- Long-haul flights capture **more cases, usually around 1–2 infected passengers.**
- **Longer flights** increase toilet use, giving **stronger wastewater signals**.

(Jones et al., 2023)



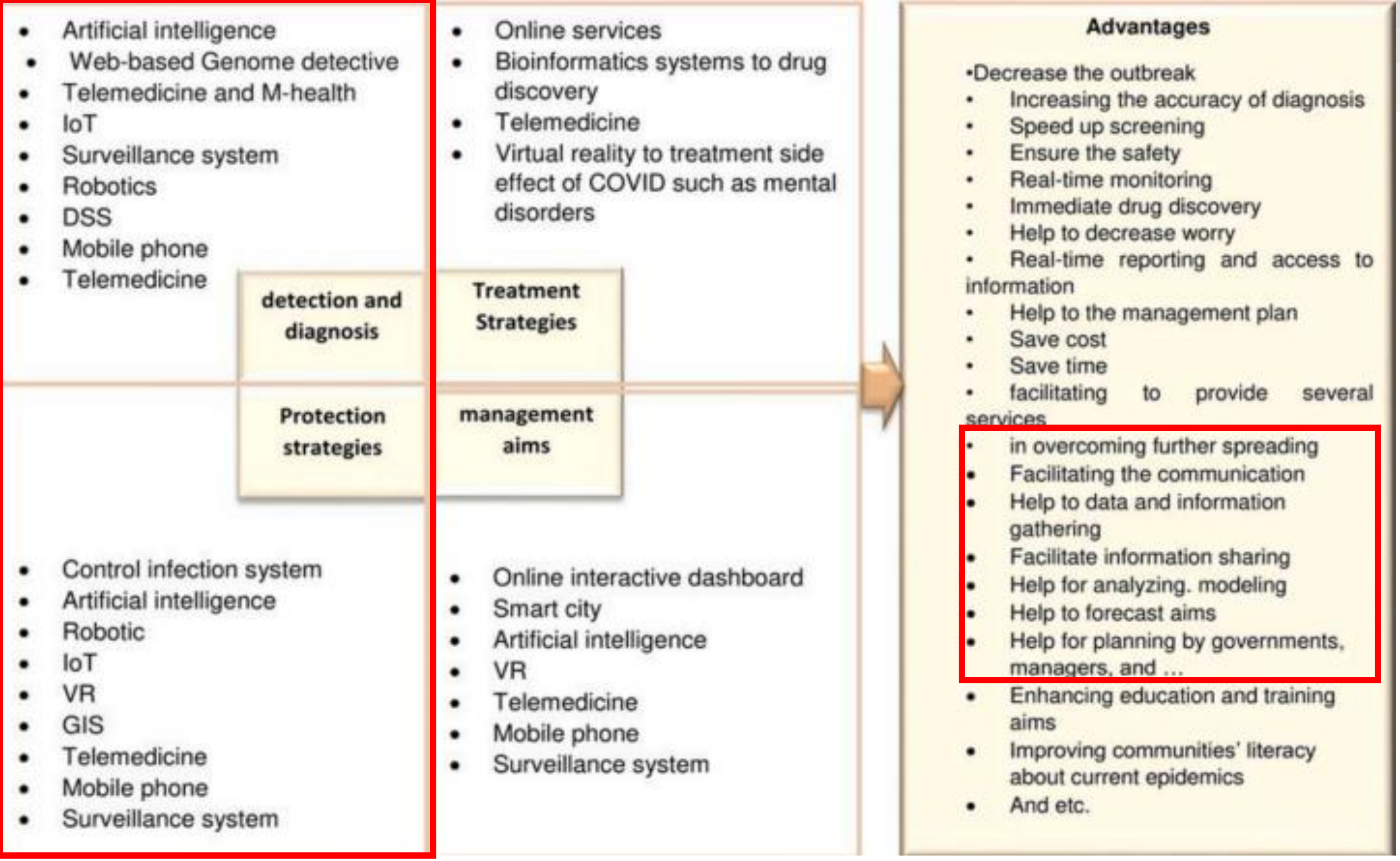
IBS–EBS Framework for Rapid Public Health Action

(WHO, 2014)

How IBS and EBS Combine to Form Epidemic Intelligence

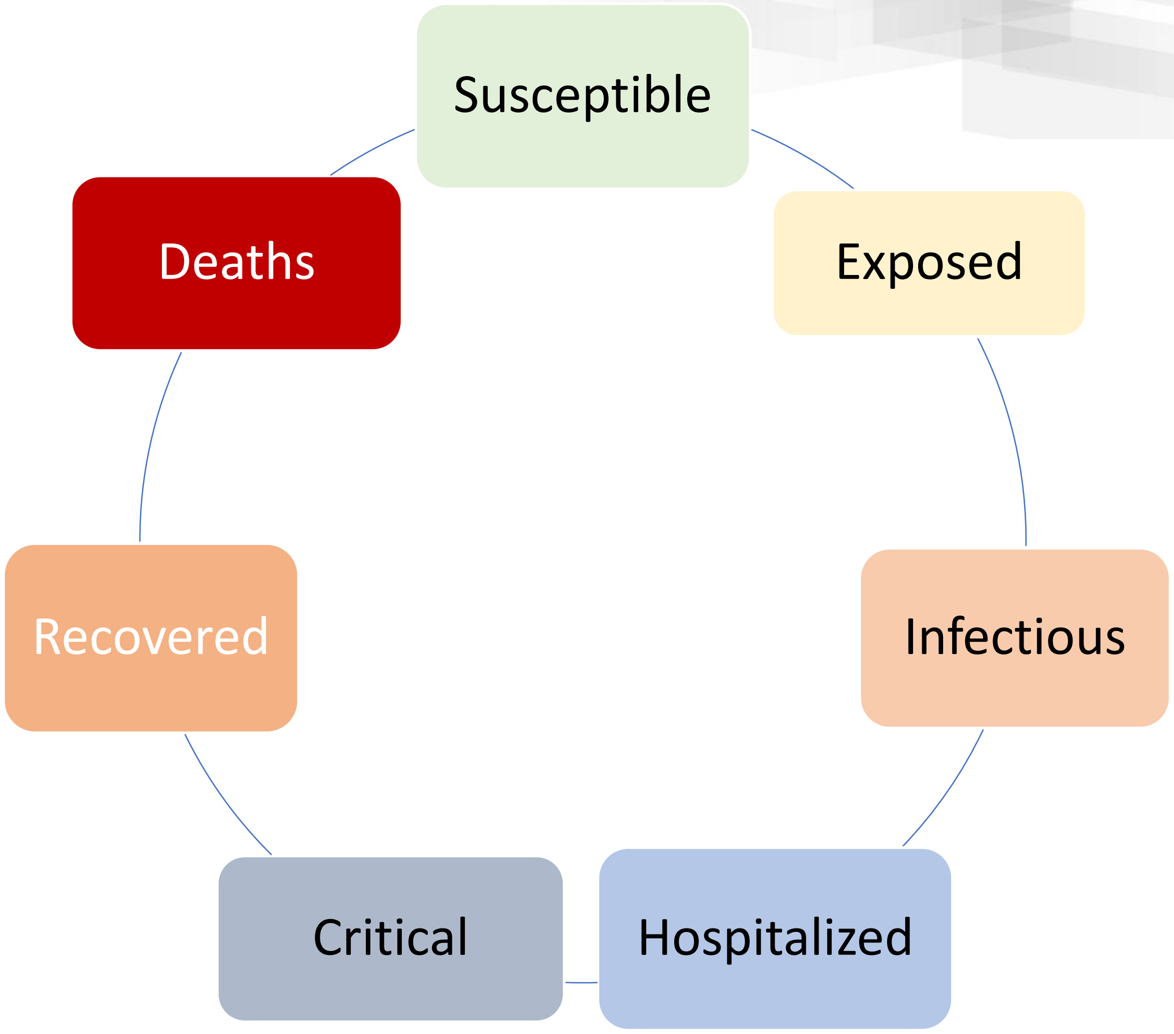
(WHO, 2014)

INTEGRATING IT TOOLS FOR EARLY DETECTION AND PANDEMIC PREPAREDNESS



(Asadzadeh et al., 2020)

- Early detection requires **smart IT tools**
- **Real-time data** improves outbreak awareness
- **Automation strengthens protection**
- **Digital health expands response** capacity
- Dashboards and modelling support early warning



(Bhuvaneswari, 2023)

SEIR – HCD MODEL

- Shows how a **disease spreads through a population**
- Estimates **risk of infected travelers on specific routes**
- Supports **early warning at airports**

Parameters and Data Needed to Run SEIR-HCD Simulations

(Bhuvaneswari, 2023)

Disease Specific Parameters

- Transmission Rate
- Incubation – infectious rate
- Recovery rate
- Detection rate
- Hospitalization proportion
- Critical illness proportion
- Mortality rate (hospitalized)
- Death rate (critical)

Air Traffic & Population Inputs

- Passenger Volume per route
- Number of flights per destination
- Infection levels at origin
- Airport catchment population
- Screening/symptom detection
- Traveler health declaration data
- Intervention measures (screening, testing, quarantine)

SEIR – HCD MODEL Outputs for Surveillance & Early Warning

(Bhuvaneswari, 2023)

Epidemiological Outputs

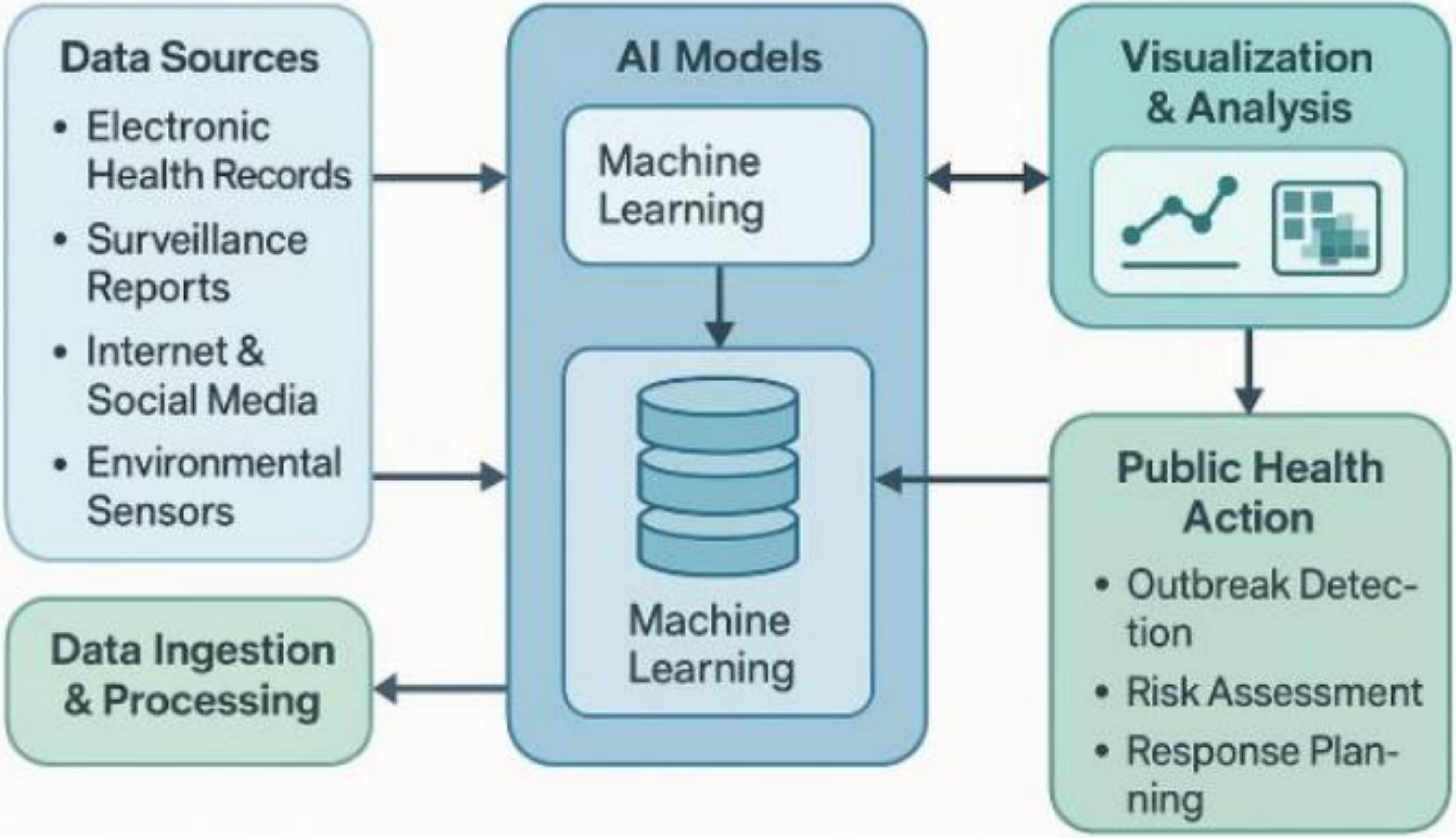
- Predicted cases
- Peak infection time
- Outbreak duration
- Expected severe and critical cases
- Expected deaths

Risk Forecast Outputs

- Importation probability per route
- Predicted infected travelers
- Passenger infection risk
- Airport vulnerability scores
- Route – based risk ranking

Decision Support Outputs

- Recommended interventions
- Early – warning Alerts
- Public health response triggers
- Resource allocation forecasts
- Scenario comparisons (with/without intervention)



How AI Transforms Data Into Early Outbreak Alerts

(Okoye, 2025)

AI TECHNIQUES SUPPORING EARLY WARNING SYSTEMS

(Villanueva-Miranda, Xiao & Xie, 2025)

Machine Learning (ML)

- SVM
- Random Forest
- Logistic Regression
- XGBoost

Deep Learning (DL)

- LSTM
- CNNs
- Transformer models (e.g., BERT).

Natural Language Processing (NLP)

- To analyze news, social media, healthcare notes
- Extracts early outbreak signals from digital data

Ensemble Models

- Combines multiple algorithms for better prediction.

Hybrid Systems

- AI + traditional epidemiological or statistical models.

Explainable AI (XAI)

- To make AI decisions transparent to humans
- LIME
- SHAP)
- Attention Visualization

AI ENABLED EARLY WARNING SYSTEM

DATA SOURCES

- Electronic Health Records
- Mobile phone mobility data
- Airline ticketing and travel patterns
- Social Media and digital platforms
- Environmental and Climate data
- Wearables and biosensors
- Airport Syndromic Screening Data
- Genomic Sequencing Data
- Climate Driven Vector Risk
- Wastewater Surveillance
- Internet Search Query Data

(Idahor et al., 2025)

AI MODELS

Predictive Models (AI)

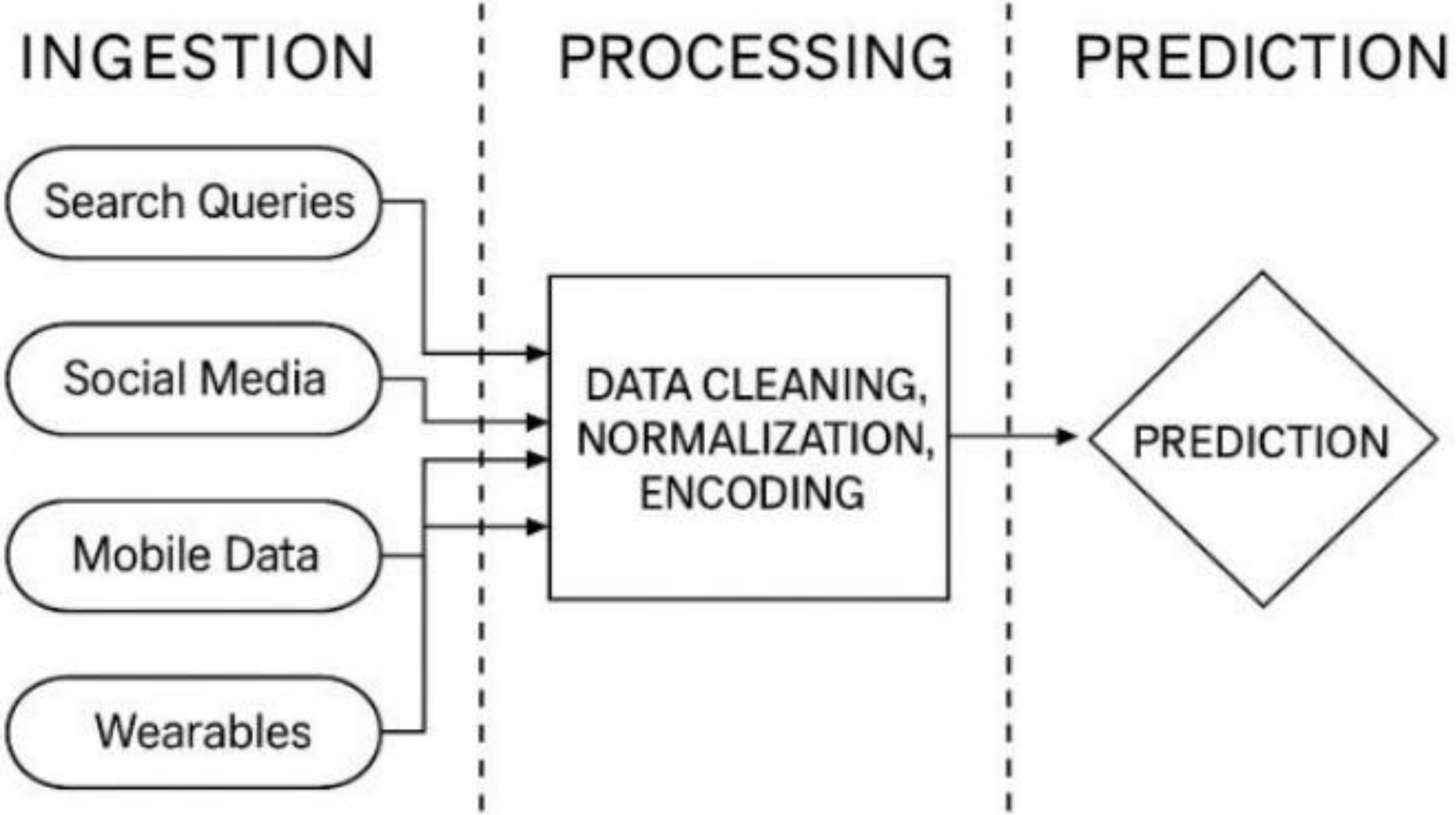
- BlueDot
- HealthMap
- GPHIN
- WHO EIOS

- Outbreak detection
- Risk Prediction
- Trend Forecasting

ACTIONABLE OUTPUTS

Real time Dashboard and Automated Alerts

- Airport Risk Scores
- Early Warnings
- Preparedness Triggers
- Flight based risk Alerts
- Cross-border coordination signals



How AI Processes Digital Signals to Predict Outbreaks

(Okoye, 2025)

Platform	Notable Outbreak	Detection Speed	Primary Data Sources	Geographic Coverage	Transparency / Accessibility
BlueDot	COVID-19 (2019–2020)	Early (9 days before WHO alert)	News reports, airline data, official health sources	Global	Low (proprietary system)
HealthMap	Ebola (2014), Zika, COVID-19	Early (within days of event)	Online news, official alerts, ProMED, user submissions	Global	High (open access platform)
Google Flu Trends	Seasonal Influenza (2008–2015)	Moderate (real-time updates)	Search engine queries	~25 countries	Low (retired, limited transparency)
ProMED-mail	SARS, MERS, Ebola	Moderate to early (manual curation)	Expert-sourced news, field reports	Global	Moderate (public, moderated content)
EIOS (WHO)	COVID-19, Monkeypox	Early (days before official reports)	Open-source news, official sources, social media	Global (194 member states)	Moderate (limited public interface)
SORMAS (Africa CDC)	COVID-19, Lassa fever	Variable (real-time updates within systems)	Case reports, lab data, syndromic inputs	Africa (12+ countries)	Moderate (government-deployed, closed)

AI Epidemic Intelligence Platforms Compared

(Okoye, 2025)

Country/Region	Digital Health Data Systems	Workforce Capacity (AI & Data Skills)	Legal & Ethical Governance	AI Integration in Surveillance	Overall Readiness Level
United States	Advanced (EHRs, APIs, syndromic systems)	High (academic and government-trained)	Moderate (state-level variability)	Moderate (CDC pilots, academia)	High
Germany	Advanced (national digital health registry)	Moderate (growing AI research base)	High (GDPR compliance, data ethics)	Moderate (predictive modeling tools)	High
India	Moderate (fragmented but improving)	Moderate (increased training initiatives)	Moderate (emerging data protections)	Low to Moderate (AI in early stages)	Moderate
Brazil	Moderate (SUS-linked data hubs)	Low to Moderate (limited AI expertise)	Moderate (legal gaps exist)	Low (limited AI in public surveillance)	Moderate
Kenya	Basic to Moderate (pilot digital tools)	Low (nascent digital health training)	Low (no AI-specific health laws)	Low (few integrated AI systems)	Low
South Korea	Advanced (integrated surveillance-EHR)	High (strong tech sector collaboration)	High (robust digital governance)	High (real-time contact tracing AI)	Very High
Nigeria	Moderate (SORMAS implementation ongoing)	Low to Moderate (Africa CDC support)	Moderate (digital health bill pending)	Low (AI pilots underway)	Moderate
Canada	Advanced (Pan-Canadian Health Data Strategy)	High (strong academic-industry pipeline)	High (data protection frameworks)	Moderate (BlueDot, academic tools)	High

Strength of National Digital Health & AI Infrastructure

(Okoye, 2025)

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AI Epidemic Intelligence Platforms Compared

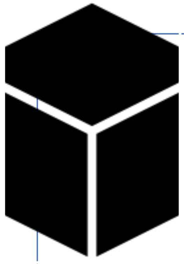
(Okoye, 2025)

KEY CHALLENGES & LIMITATIONS OF AI

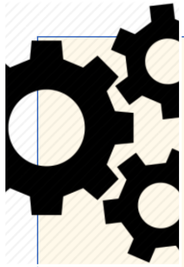
(Villanueva-Miranda, Xiao & Xie, 2025)

Data Quality gaps & Missingness

Bias in digital and clinical datasets



Black-box behaviour of AI models



Infrastructure + System connectivity constraints

Privacy, consent & Equity considerations

Need for human oversight to validate alerts


ASANTE SANA