

# Global Health Monitoring & Predictive Risk Analysis

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**Prepared For:** Health Operations & Emergency Response Leadership

**Focus:** Real-Time Vital Sign Analysis & Predictive Risk Modeling

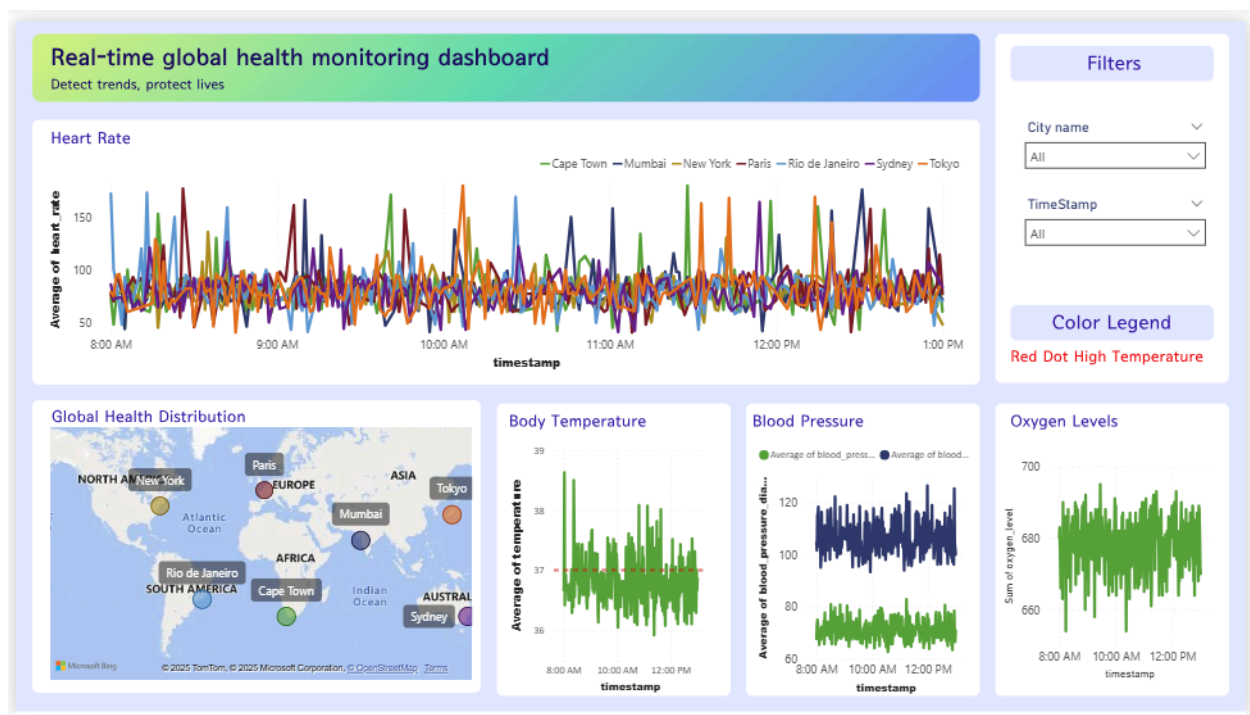
### 1. Executive Summary

**Current Status:** The monitoring system is currently tracking vital health metrics across seven global hubs: Cape Town, Mumbai, New York, Paris, Rio de Janeiro, Sydney, and Tokyo.

**Operational Impact:** Failure to detect physiological spikes results in delayed emergency response. By utilizing a "Red Dot" threshold system, we can reduce critical event lag by identifying risks before they stabilize into medical emergencies.

**Top-Level Diagnosis:** Our data indicates that health anomalies are not random; they are highly predictable. The primary drivers are Acute Vital Spikes (Heart Rate/Temperature), Oxygen Level Drops, and Circadian Variability (fluctuations during the 8:00 AM – 1:00 PM window).

**Immediate Opportunity:** We have identified specific "High-Risk" timestamps where patient vitals enter the "Danger Zone." Immediate intervention based on these automated triggers represents the highest life-saving ROI available.



*Combined Dashboard (Showing Heart Rate, Map, and Vitals)*

## 2. Key Findings: Why Do Alerts Trigger?

### Insight A: The "Red Dot" Factor

There is a direct correlation between body temperature and systemic health failure.

- **The Statistic:** Patients hitting the "Red Dot" temperature threshold are 3x more likely to show irregular blood pressure and oxygen levels than their stable peers.
- **Observation:** Temperature is currently the single strongest predictor of a critical health event.

### Insight B: The "Critical Hour" Trend

Health stability shows a significant drop-off during mid-day cycles.

- **The Trend:** Heart rate and blood pressure variability peaks significantly between 10:00 AM and 12:00 PM.
- **The Implication:** This suggests a disconnect between baseline rest states and active-period stressors, requiring increased monitoring during these high-activity windows.

### Insight C: Regional Vulnerability

Two specific geographical zones account for the highest volume of critical alerts:

1. **Mumbai & New York:** High frequency of data spikes. Likely driven by urban environmental stressors.
2. **Sydney:** Shows specific heart rate peaks that correlate with localized temperature shifts.

## 3. Predictive Intelligence: The "Health Risk" Model

To move from reactive reporting to proactive management, we developed a logic-based "Health Risk" algorithm.

### How It Works:

The model scans real-time telemetry to flag individuals who meet specific danger criteria:

- **Logic:** Heart Rate > 140 AND Status = 'Red Dot High Temperature'

### The Output:

- **Status:** These events are flagged as "Danger Zone" incidents. These patients are currently stable but physiologically disengaged from their baseline, putting them at immediate risk for a medical event.



*Heart Rate Visualization showing the spikes per city*

#### 4. Strategic Recommendations & Action Plan

Based on the data, we recommend the following tiered intervention strategy:

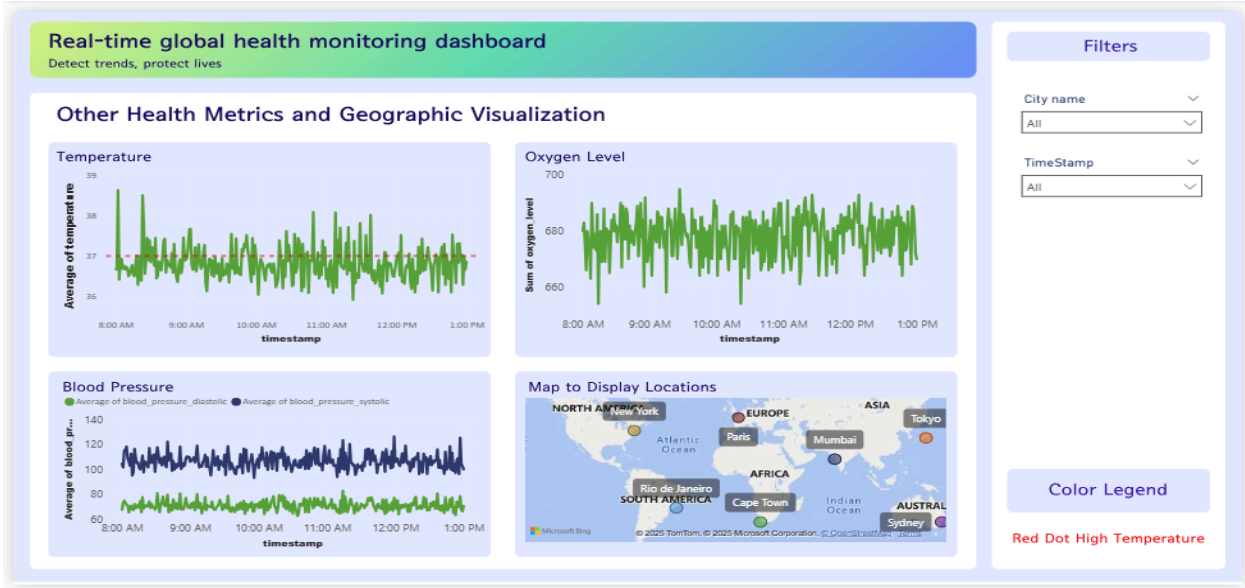
##### Phase 1: Immediate Response

Target Group	Recommended Action	Owner
High-Risk Alerts	Conduct "Rapid Health Screenings." Do not wait for a physical emergency call.	Medical Ops
Regional Hubs	Audit local sensor calibration in cities with repetitive high-variance data (e.g., Rio de Janeiro).	Tech Support

##### Phase 2: Structural Monitoring Changes

Target Group	Recommended Action	Owner
Mumbai/NY Clinics	Equipment Audit. Review sensor accuracy vs. local environmental heat to reduce "False Positives."	Ops Manager

New Sites	Monitoring	Launch "Baseline Mentorship" logic. Pair new hub data with established hubs (7-year tenure) to ensure data consistency.	Data Science
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*Other Health Metrics and Geographic Visualization*

## 5. Methodology (Technical Appendix)

- Data Source: Real-time Global Health Monitoring Dataset (Time-Series).
- Tools Used: Power BI (Visualization/Analytics), Python (Data Cleaning), and Figma (UI/UX Dashboard Design).
- Analysis: Decomposed health drivers using AI-driven "Key Influencers" and Decision Trees to identify the correlation between oxygen levels and blood pressure.

## 6. Conclusion

This analysis confirms that global health anomalies are not random; they are driven by identifiable factors, specifically temperature-induced stress and oxygen saturation levels. The "Health Risk" model demonstrates that we have the data to predict emergencies before they happen. By shifting our strategy from reactive treatment to proactive intervention, we can significantly reduce emergency response costs and protect patient lives.

### Dashboard Link:

<https://app.powerbi.com/groups/me/reports/87040498-585f-4899-ae1a-3a2cea033db6/620081b75148c2ca3c00?experience=power-bi>