

The Value Proposition of Collaborative Research Partnerships: Industry–Academia– Government for Public Health Impact

2026 NCR Public Health Preparedness & Response Academy

February 2026



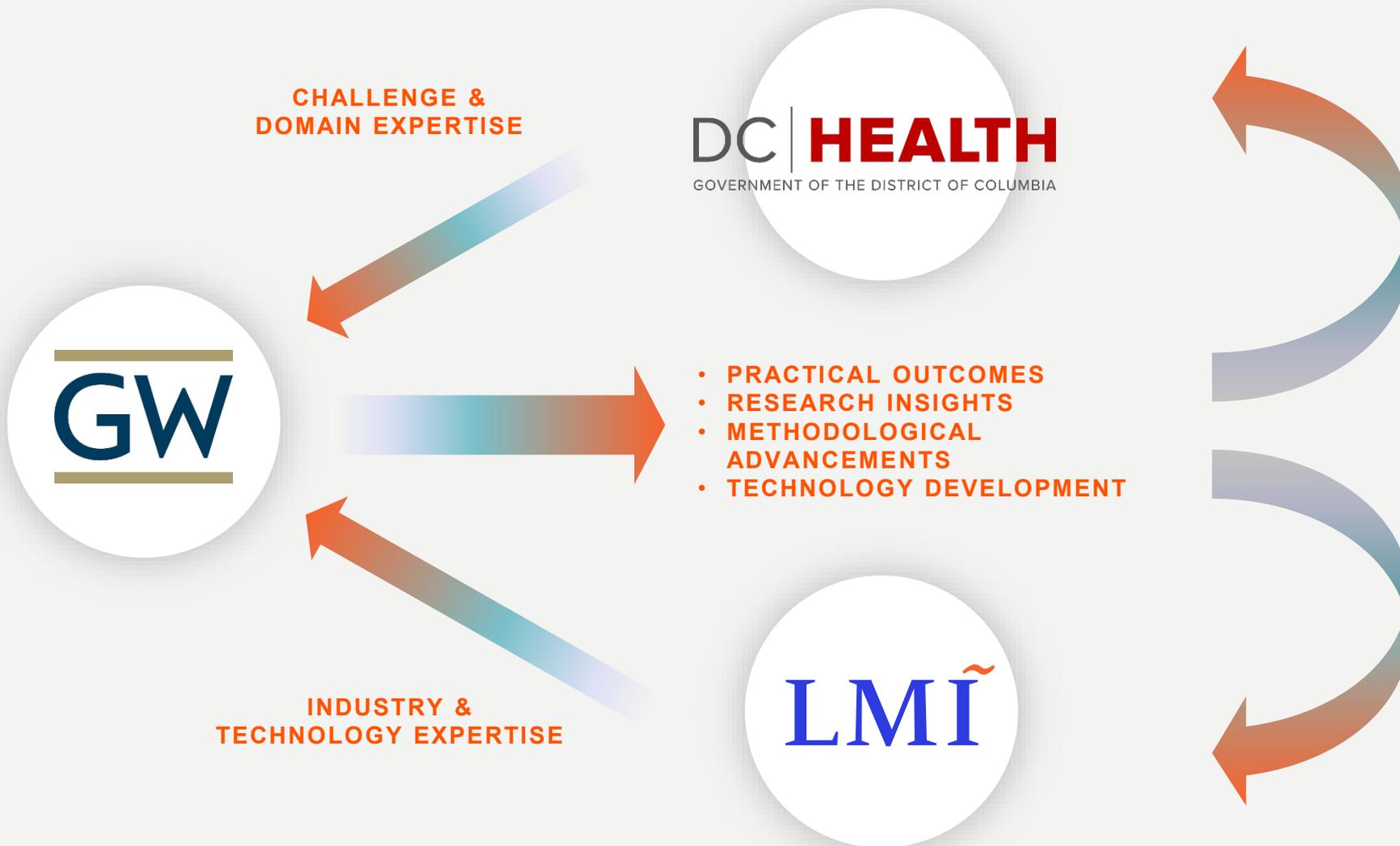
AGENDA

- **Dr. Kristin Raphel (DC Health) –**
 - Value proposition of innovation partnerships with Academia + Industry
- **Dr. Erica Gralla (George Washington University) –**
 - “Case Definition Analysis and Implications for Allocating Heat Emergency Resources in Washington, D.C.”
- **Dr. Brant Horio (LMI) & Sam Liu (LMI) –**
 - Technology demonstration for bridging collaborative research to practical application
- **Dr. Kristin Raphel (DC Health) –**
 - Ongoing research with George Washington University + LMI
 - “Emergency Department Crowding: Evidence-based Assessment”

COLLABORATIVE RESEARCH

Industry Technology and Expertise against Real-World Challenges

An experiential opportunity to apply classroom learning with advanced methods for community impact.





Case Definition Analysis and Implications for Allocating Heat Emergency Resources in Washington, D.C.

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George Washington University

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Research Advisor: Dr. Erica Gralla

Date: 28 April 2025

Problem Statement

As summer heat increases, identifying heat-related illness (HRI) and optimizing the response to it are urgent needs in Washington, DC.



Patient Care Report

Narrative

primary
impression

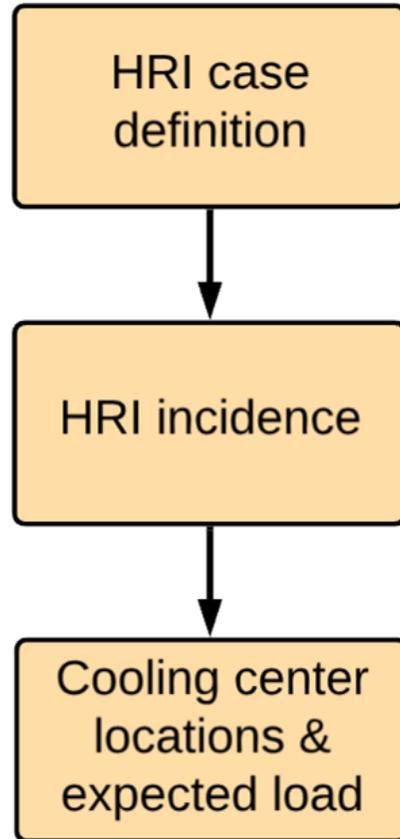
**Chief
Complaint**

secondary
impression

incident
location, vitals,
patient ID, etc

symptom code

Why are case definitions important?

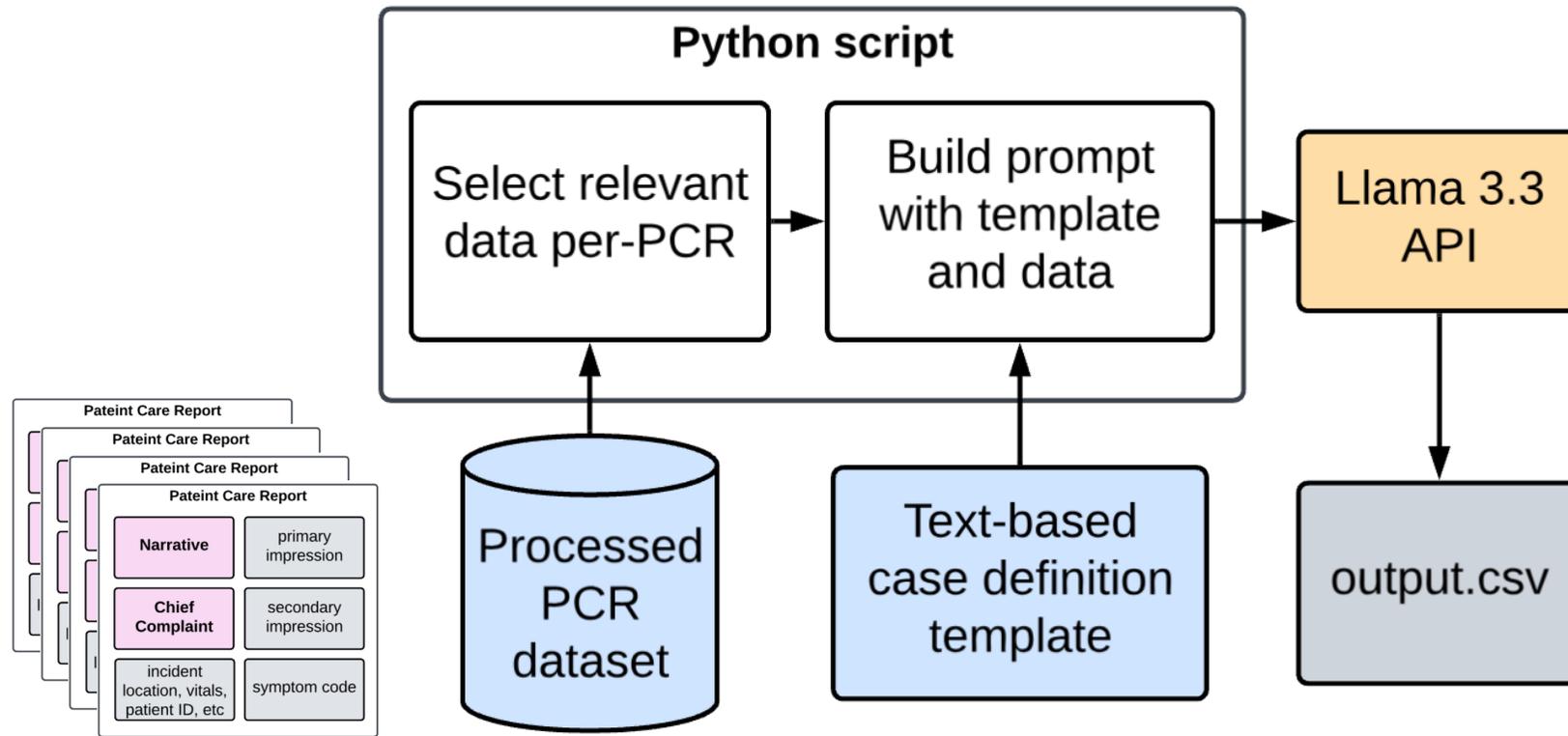


Research Questions

LLM = Large Language Model, e.g. ChatGPT

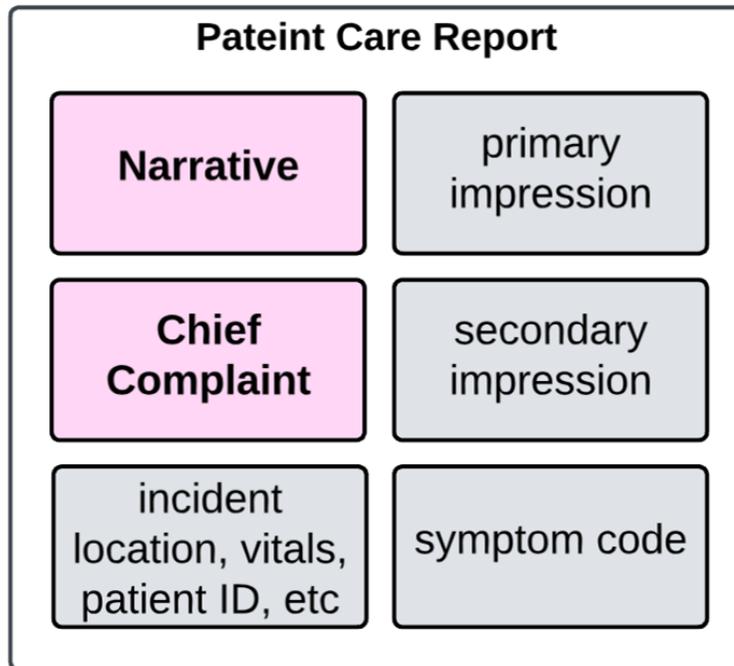
1. How well can an LLM classify HRI cases leveraging EMS narrative data?
2. How do three existing HRI case definitions compare with each other and with the novel LLM definition?
3. How do the optimized cooling center locations change across definitions?

LLM Definition Application Method



Summers, 2018-2024

RQ1: LLM Definition Development



Definition	Contents of Prompt in LLM Definitions
D1	Narrative
D2	Narrative, Chief Complaint
D3	Narrative, Chief Complaint, Primary & Secondary Impression Codes, Symptom Code
D4	Narrative, Chief Complaint, Primary & Secondary Impression Codes, Symptom Code, Narrative Examples of Positive and Negative HRI
<i>D5 in progress: + outside temperature</i>	

RQ1: Definition 4 and LLM Prompt

You are an expert emergency medicine physician solving a complex medical case.
You will analyze the narrative portion of a patient care report.

Heat emergencies present as a spectrum of symptoms, beginning with sweaty skin, flushing, and lightheadedness/dizziness. They progress to dry skin, weakness, nausea/vomiting, muscle cramping, and increasing heart rate. Severe cases (heat stroke) involve neurological symptoms, such as a gradual decrease in consciousness. Not eating or drinking increases risk or severity of developing a heat-related illness. Young and elderly patients may show minimal signs until heat stroke is fully developed. These populations are at higher risk and should be monitored closely.

An example of a narrative that is not heat related incident is: {example}
An example of a narrative that is a heat related incident is: {example}

Given this information, determine whether the following patient report, with the primary and secondary impressions from the provider, indicates a heat-related illness:

Narrative:
Primary Impression:
Secondary Impression:
Chief Complaint:
Symptom Code:

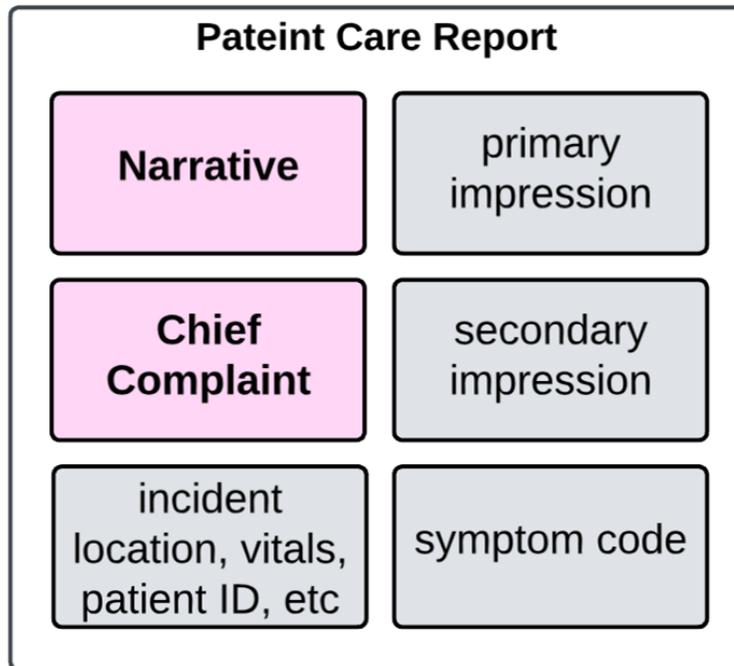
Answer only with YES or NO.

Instructions for LLM

Definition of HRI w/
examples

Information from the
PCR being processed

RQ2: HRI Case Definitions



Definition	Contents of Prompt in LLM Definitions
NHTSA/ NEMESIS	Most conservative: very small number of ICD-10 codes
Keyword	Searches narrative for a set of predefined keywords
Signs & Symptoms	Most broad: a large set of ICD-10 codes
LLM	Developed by this project. Uses a LLM to examine the narrative and other information

RQ3: Geographic Optimization

- Inputs HRI and potential CC coordinates
- Outputs the most optimal CC locations to address HRI
- Subject to minimum total distance between HRI and CCs, per definition

P-Median Problem

$$\min \sum_{i \in I} \sum_{j \in F} d_{i,j} x_{i,j} \quad (1)$$

Subject to

$$x_{i,j}, y_j \in \{0, 1\} \quad (2)$$

$$d_{i,j} = |\text{lat}_F(j) - \text{lat}_I(i)| + |\text{long}_F(j) - \text{long}_I(i)| \quad (3)$$

$$\sum_{j \in F} x_{i,j} = 1, \quad \forall i \in I \quad (4)$$

$$x_{i,j} \leq y_j, \quad \forall i \in I, j \in F \quad (5)$$

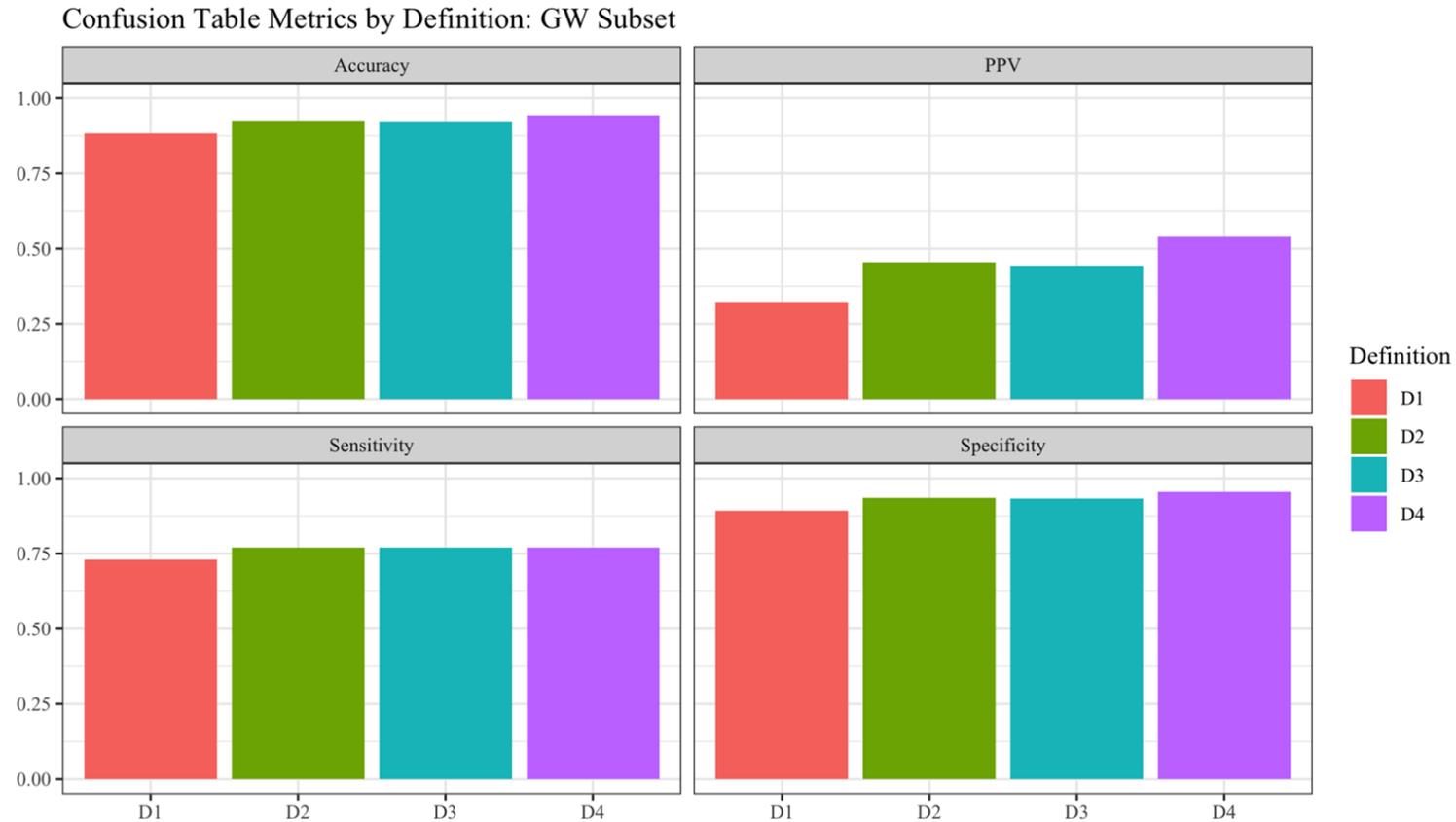
$$\sum_{j \in F} y_j = p \quad (6)$$

Model ran in AMPL using solver CPLEX

Metrics of comparison

Metric	Formulation	Interpretation
Sensitivity/ Recall	$TP / (TP + FN)$	Ability to correctly identify true positives
Specificity	$TN / (TN + FP)$	Ability to correctly identify true negatives
PPV/ Precision	$TP / (TP + FP)$	Proportion of positive predictions that are correct
NPV	$TN / (TN + FN)$	Proportion of negative predictions that are correct
Accuracy	$(TP + TN) / (TP+TN+FP+FN)$	Overall correctness of the model's predictions

Developing the LLM-based case definition



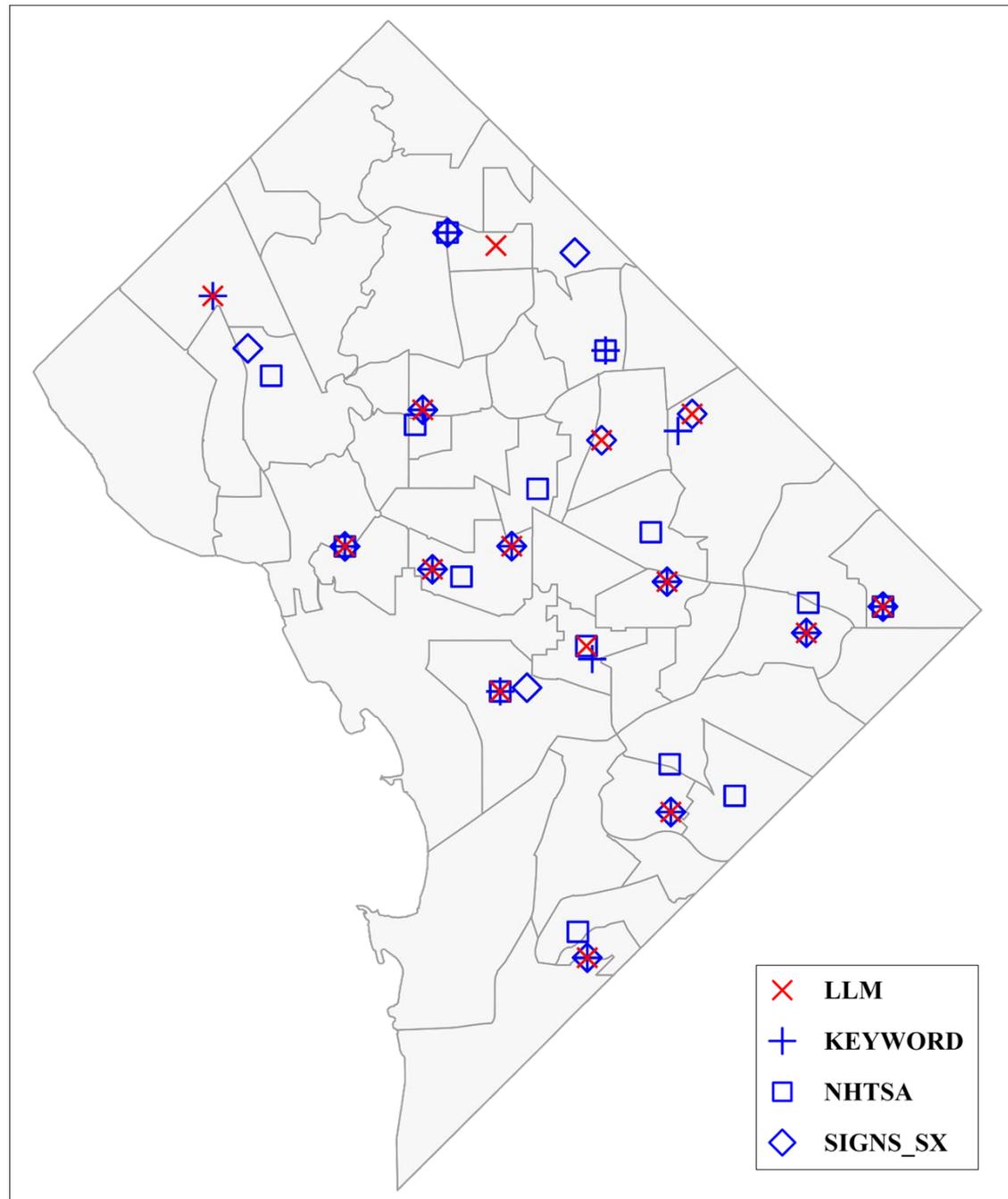
More context in the LLM prompt returned better results

Comparing LLM-based case definition to others

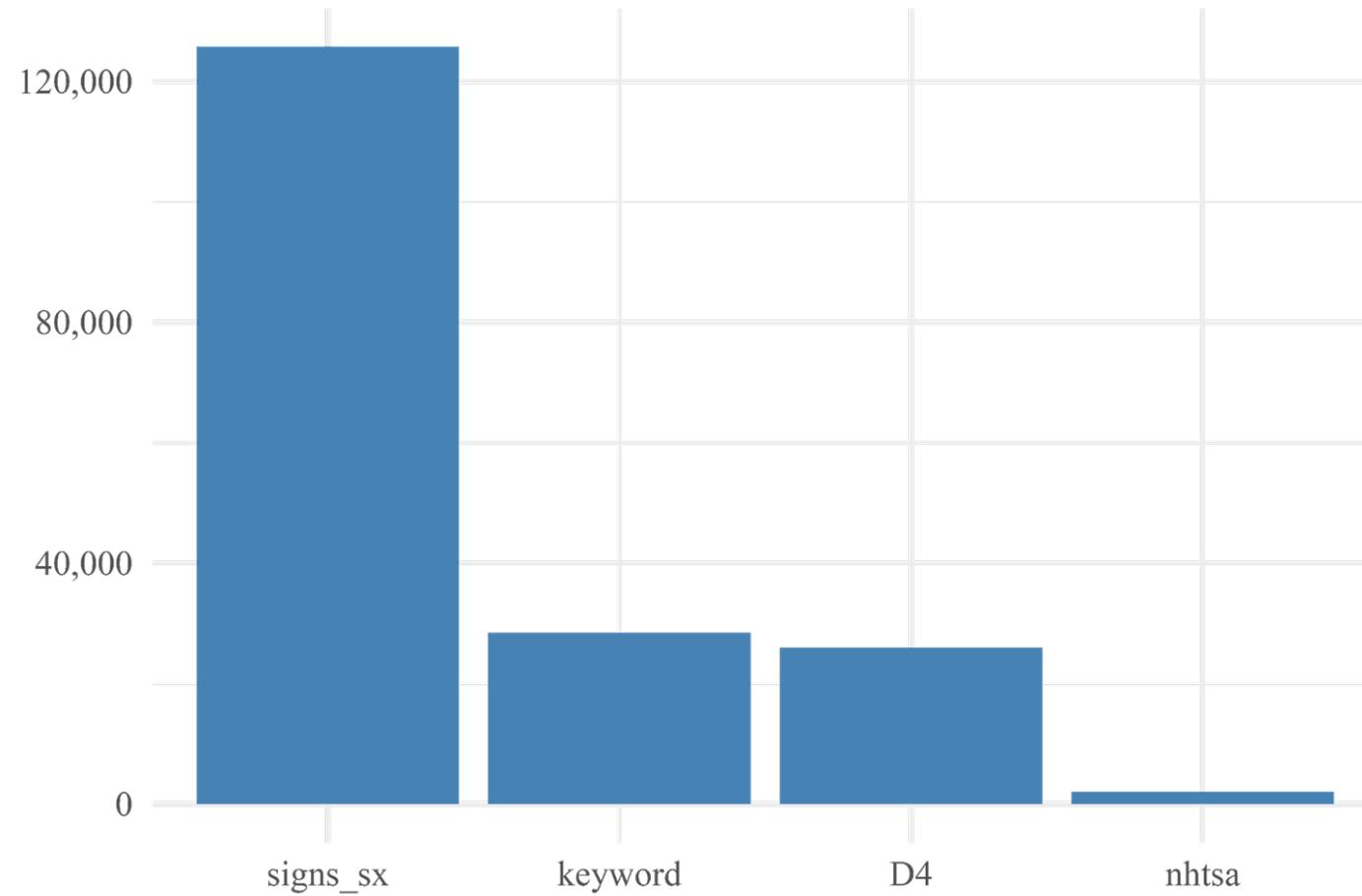
Definition	GW Classification Subset: LLM Definition Comparison				
	<i>Sensitivity/ Recall</i>	<i>Specificity</i>	<i>PPV/ Precision</i>	<i>NPV</i>	<i>Accuracy</i>
nhtsa	0.15 !	0.99	0.67	0.94	0.940
signs_sx	0.46	0.73	0.11	0.95	0.717
keyword	0.42	0.94	0.31	0.96	0.902
LLM	0.77	0.95	0.54	0.98	0.942

LLM has the best all-around performance compared to existing definitions

Across definitions, CC activations are more similar than different, though NHTSA differentiates itself with the most solo activations.



HRI per Definition



Cooling centers can be expected to address vastly different magnitudes of HRI depending on the case definition.

Conclusion

Our results show (1) a proof of concept and validation that LLMs can apply case definitions for public health surveillance and (2) describes operational implication of case definitions (cooling center locations, case loads).

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Deployment Demonstration of HRI Research within Operations



Mission-ready AI to accelerate impact, automate workflows, and enhance decisions—built for the scale, security, and compliance needs of government.

Federal agencies are being asked to manage rising workloads and fragmented data with limited resources, while still meeting strict security and compliance requirements.

LIGER® integrates secure generative AI into everyday workflows to help streamline operations, support research and analysis, and automate routine documentation and knowledge tasks.



Secure & controlled data access

User-friendly document management with granular, role-based access controls—enabling secure collaboration on sensitive workflows.



End-to-end automation at scale

Build and run repeatable processes that streamline tasks and improve consistency across the organization.



Cost-efficient AI performance

Minimize compute usage with retrieval-augmented generation, reducing costs without compromising output quality.



Collaboration built in

Shared collections, commenting, and team visibility support how government teams actually work—together.

Demonstrating the GWU + DC Health case-definition approach as a practical workflow using LLM technologies



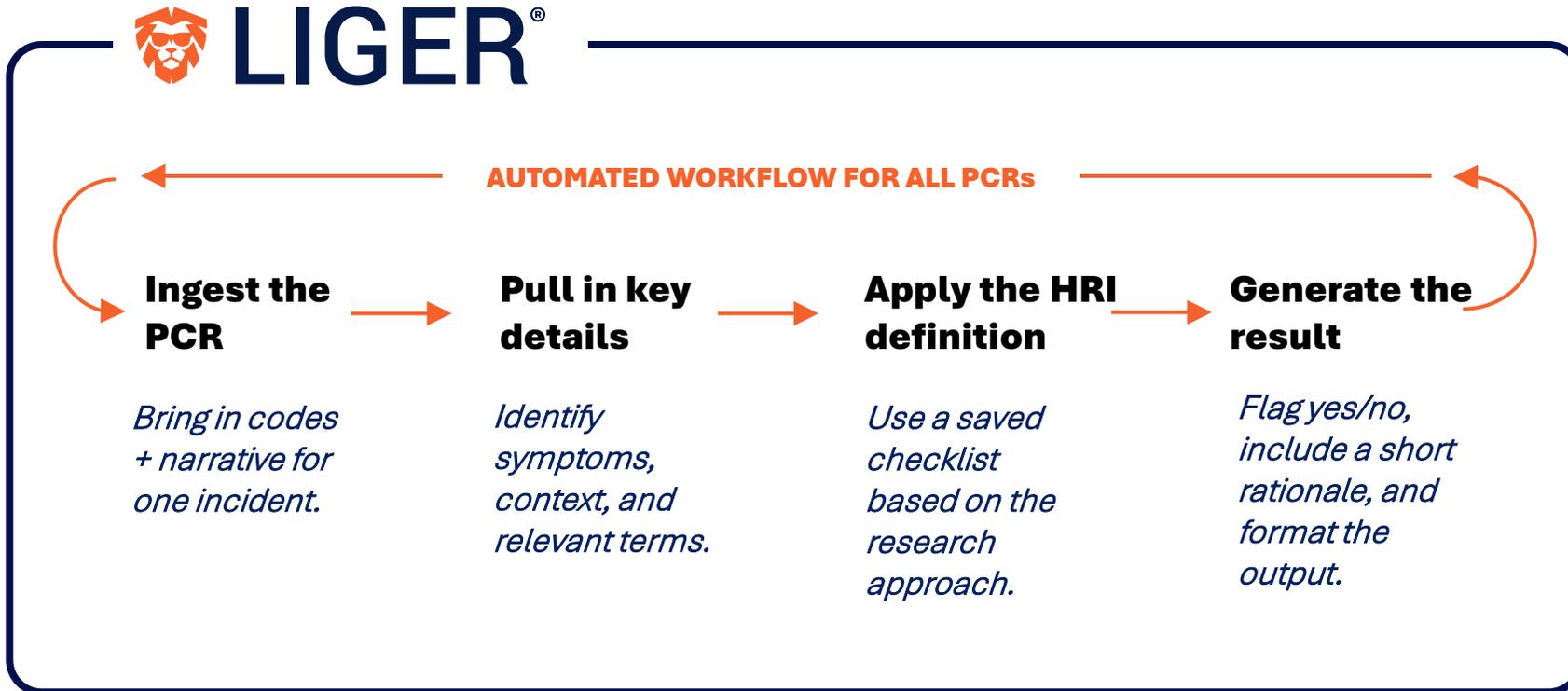
A repeatable workflow that reads each PCR, applies a saved case definition, and produces a review-ready result.

Synthetic PCR Data

“Safe, controlled examples that behave like real PCRs.”

Real-world Data Streams

“Same workflow, secure connection to live sources when needed.”



PCR Evaluation & Report(s)

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Demo

Emergency Department Crowding

Evidence-Based Assessment

Dr. Kristin Raphel

BACKGROUND

Washington D.C.



Avg Waiting Room Time:
5hr 29min (2023)



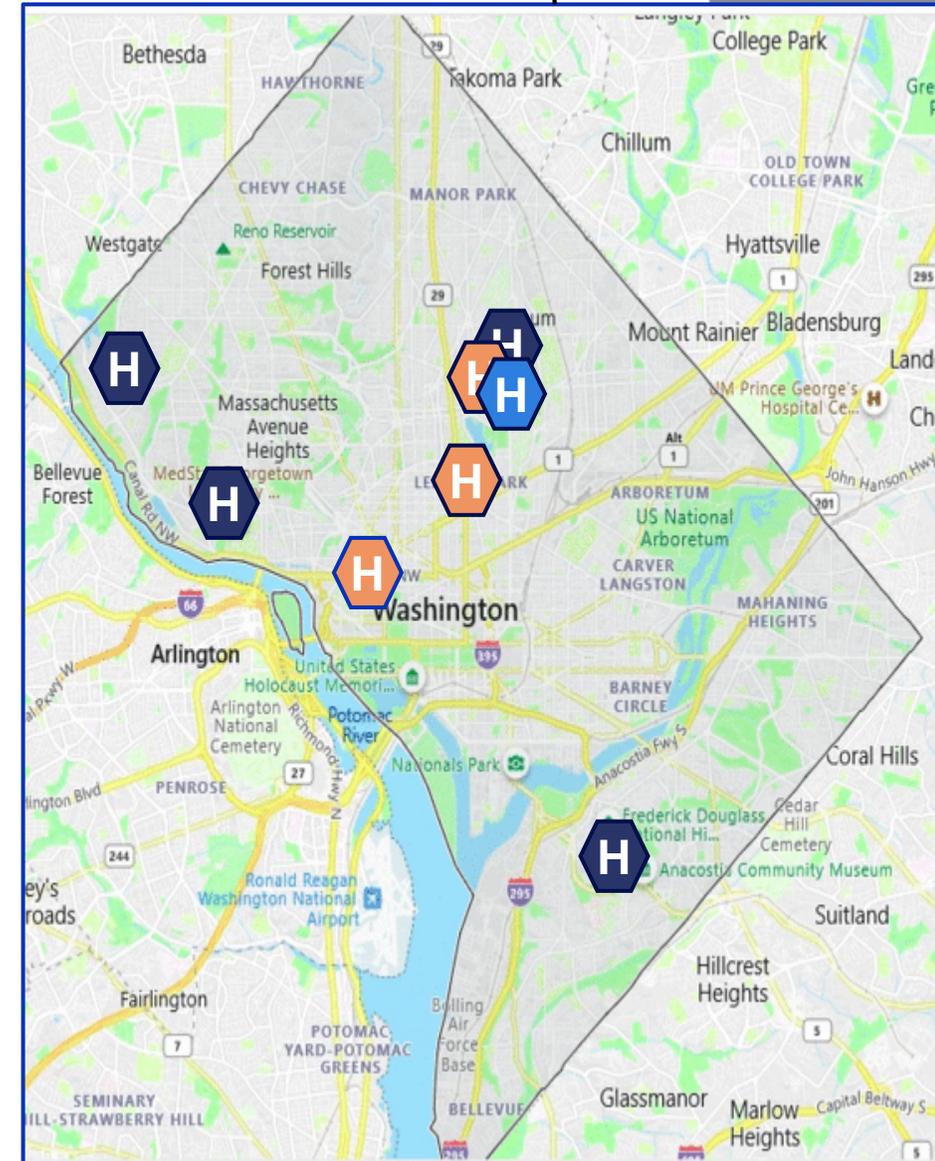
Avg. Ambulance Wait Time:
1hr 45min (2023)

- ❖ ED crowding leads to poor patient outcomes
- ❖ ED crowding at one hospital affects all other hospitals
- ❖ ED crowding leads to fewer available 9-1-1 ambulances

But...

... what causes ED crowding?
... and how crowded is too crowded?

7 District hospitals



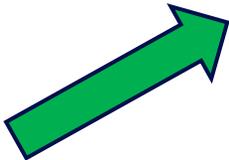
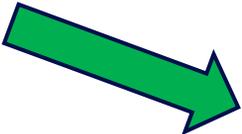
= Trauma = Pediatric Trauma

Input

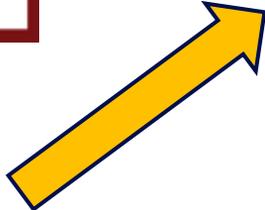
Throughput

Output

"... ED crowding is a local manifestation of a systemic disease"
- Hoot and Aronsky, 2008



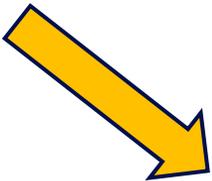
Emergency Department



Other area hospitals



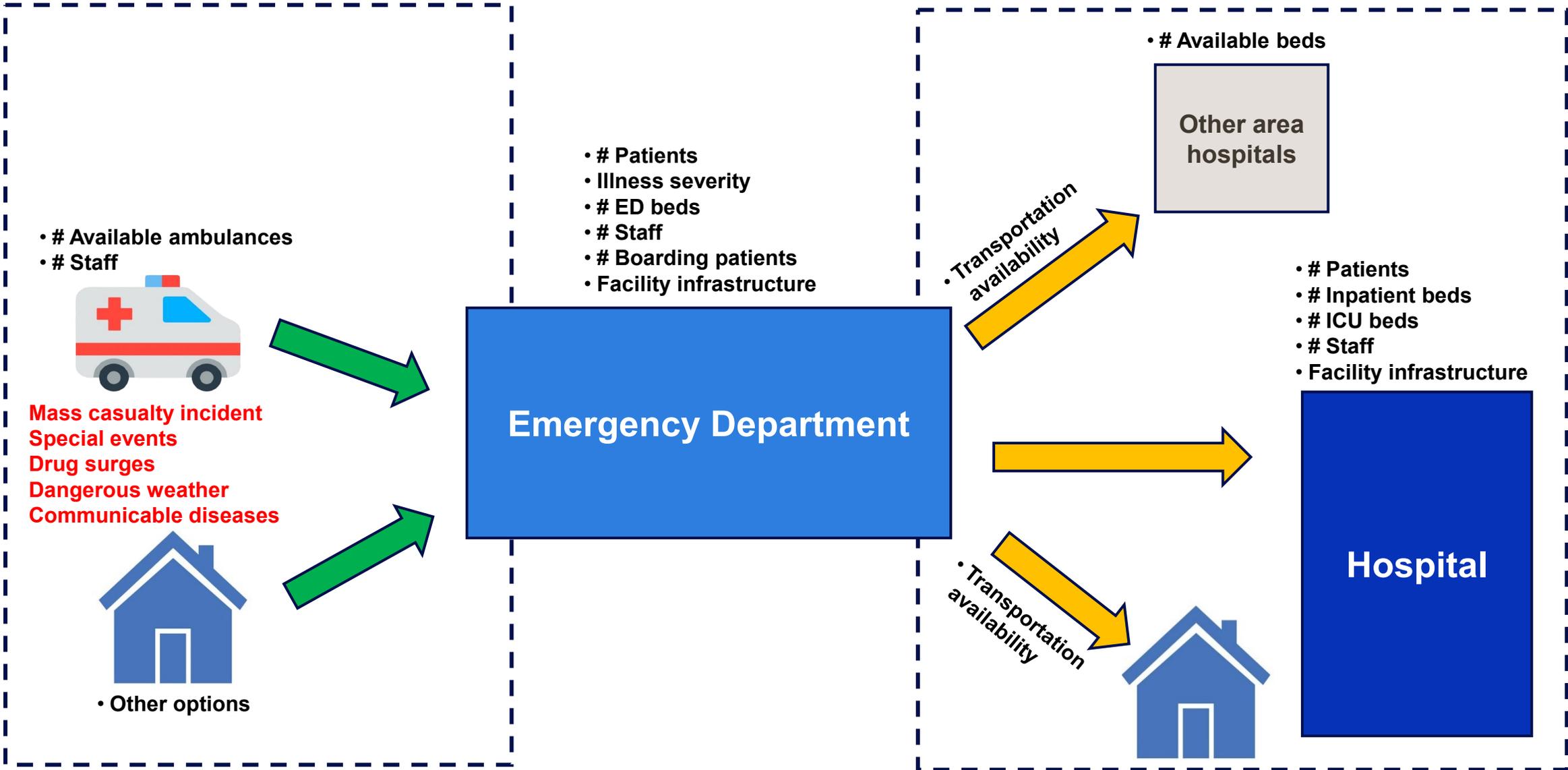
Hospital



Input

Throughput

Output



DC Health – GW Capstone Project

But...

... what causes ED crowding?
... and how crowded is too crowded?

Objectives:

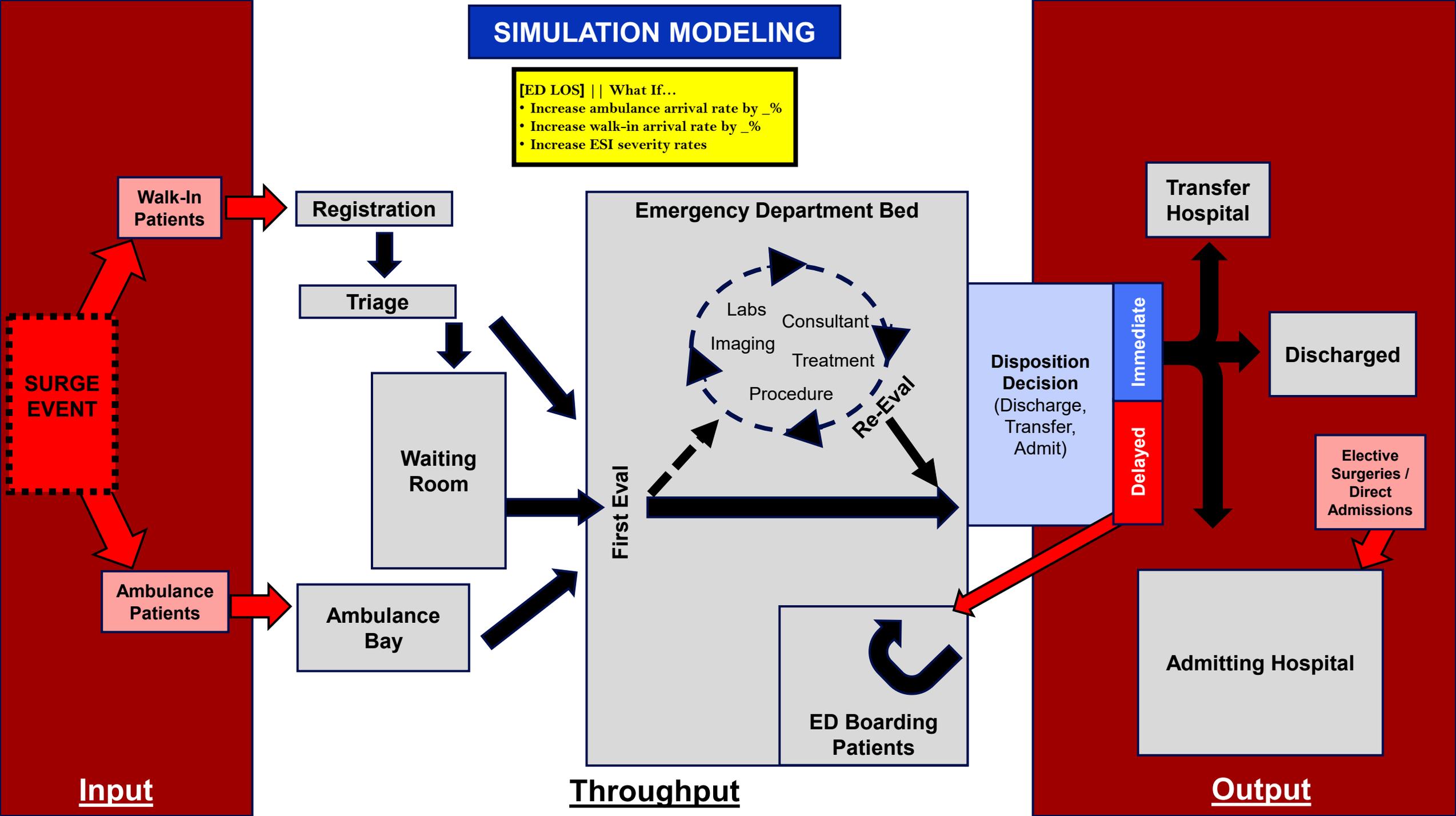
- Define which ED crowding factors are **most** associated with adverse patient outcomes
- Develop an evidence-based formula to indicate ED crowding thresholds
- Establish an ED crowding threshold that may activate surge planning activities (e.g., *Ambulance diversion*)
 - *Must be balanced with anticipated reactionary crowding at other District EDs*



SIMULATION MODELING

[ED LOS] || What If...

- Increase ambulance arrival rate by _%
- Increase walk-in arrival rate by _%
- Increase ESI severity rates



Input

Throughput

Output

DC | HEALTH

GOVERNMENT OF THE DISTRICT OF COLUMBIA

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 dchealth.dc.gov

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