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Leveraging AI to Advance Public Health Data Infrastructure

Aug. 18, 2025 | 2025 ARC Preconference

SHAPING TOMORROW'S PUBLIC HEALTH TODAY.

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Session Objectives

- Understand the foundational concepts of AI and how it can be applied to public health.
- Explore real-world applications of GenAI in public health through case studies.
- Recognize challenges and best practices in implementing GenAI solutions in public health settings.

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Agenda

1. Understanding AI in Public Health
2. Speaker Introductions
3. PHA Speaker presentations showcasing GenAI being used in Public Health
4. Q&A

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Understanding AI in Public Health

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Key Definitions

Artificial Intelligence (AI) is the development, implementation, and use of computer systems that can perform tasks that typically require human intelligence. AI describes technology that makes computers (seem to) act rationally.

Machine learning (ML) allows a computer to analyze data to do a task without being explicitly programmed. Common functions of machine learning are to (1) find patterns, like groupings of similar items and (2) to guess or predict an output based on a set of inputs.

Narrow AI also known as “weak” or “traditional” AI, focuses on performing specific tasks within a limited domain, such as image recognition, speech synthesis, or playing chess. Narrow AI has been in use for decades (decision support, google searches)

General AI refers to highly autonomous systems that feel like they possess human-level intelligence and can handle various cognitive tasks across different domains. Large language models (LLMs) are the major advancement in general AI.

- **Generative AI (GenAI)** refers to artificial intelligence systems that can create new, original content, such as text, images, or music, by learning patterns and structures from existing data.

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Key Definitions

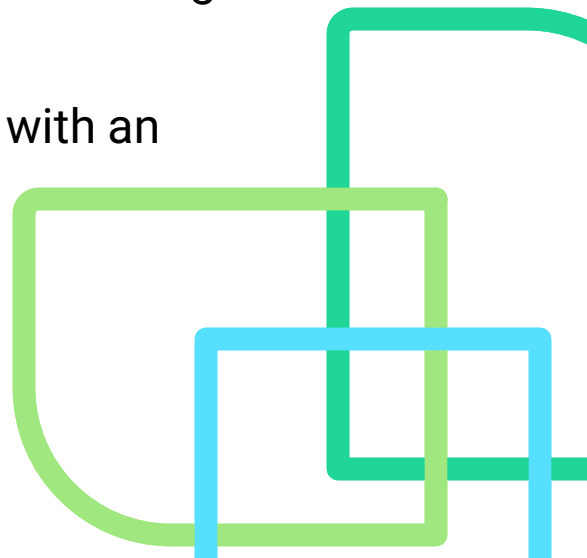
Large language models: These are advanced AI models that can understand and generate human-like text based on the patterns and structures they learn from vast amounts of data

Text chunking and vectorization/vector store: This involves breaking down text into smaller chunks and converting them into numerical vectors that can be stored and processed by AI models

Retrieval augmented generation (or RAG) approach: This is a method that combines the strengths of retrieval-based and generation-based models to produce more accurate and contextually relevant response

Deterministic variables: These are variables in a model that have a fixed value and do not change based on probability

Probabilistic variables: These are variables that have a range of possible values, each with an associated probability



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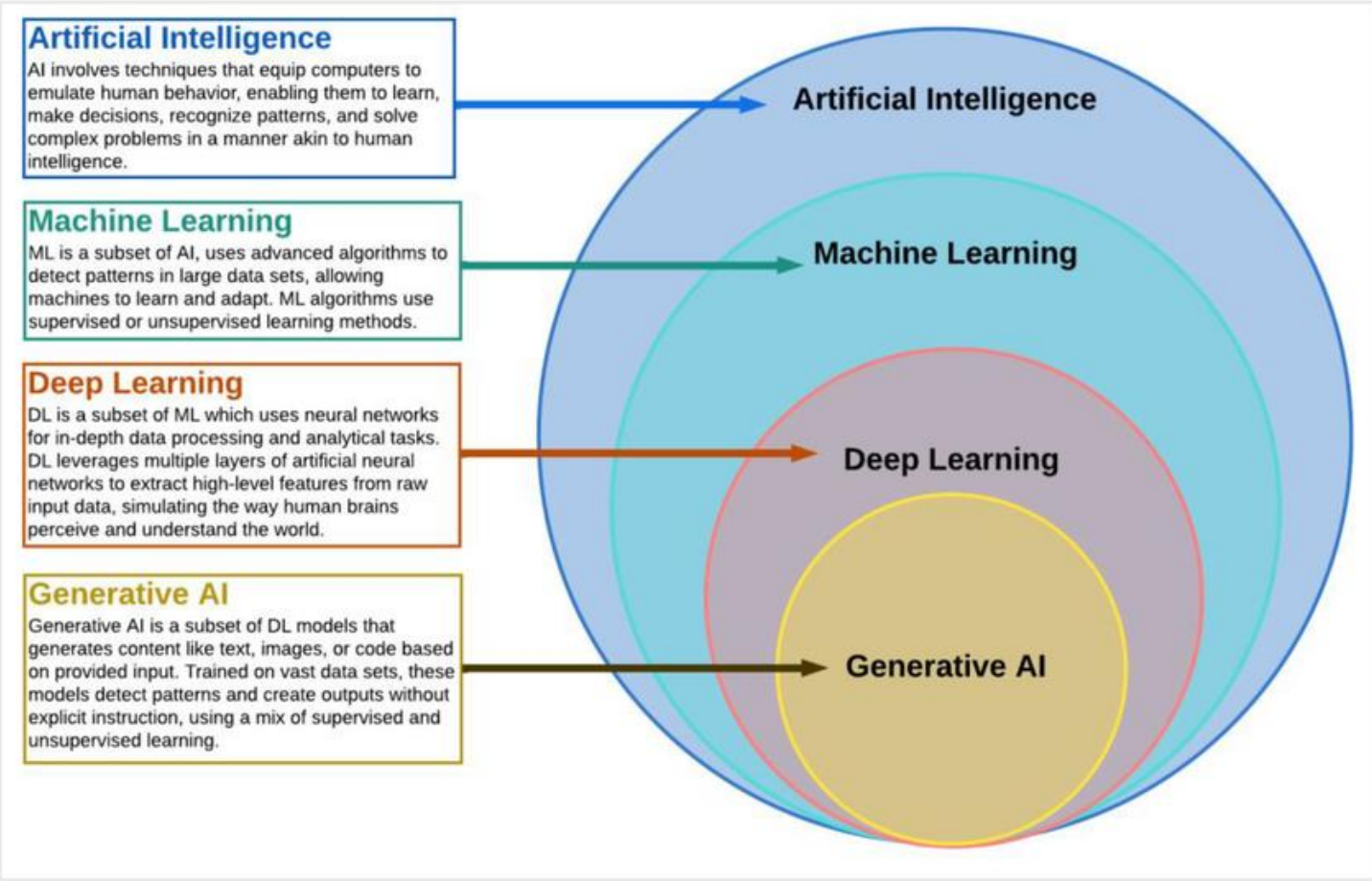
A Comparative View of AI, ML, Deep Learning, & GenAI



Source: *The Application of AutoML Techniques in Diabetes Diagnosis: Current Approaches, Performance, and Future Directions - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/A-comparative-view-of-AI-machine-learning-deep-learning-and-generative-AI-source_fig1_373797588 [accessed 14 Aug 2025]*

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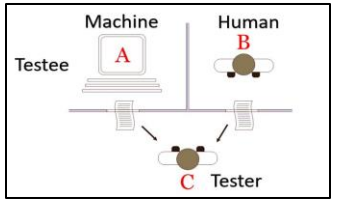

Turing Test (1950)

A vision of what's to come

IBM Watson (2011)

AI defeats humans in Jeopardy!

OpenAI's GPT-3 Release (2020)

AI is capable of generating human-like text

Proliferation of genAI (2023)

GenAI has expanded across industries and many people use AI daily

America's AI Action Plan (2025)

White House unveiled comprehensive AI Strategy in July of 2025

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Meet the Speakers

Dejan Jovanov
Chief Data & Informatics Officer,
Division of Patient Safety & Quality,
Office of Policy Planning & Statistics
Illinois Department of Public Health

Stephanie Meyer, MPH
Epidemiology & Data Unit Supervisor,
Emerging Infectious Diseases
Epidemiology & Response Section,
Infectious Disease Epidemiology,
Prevention, & Control Division
Minnesota Department of Health

Jim Daniel, MPH
Leader of State and Local
Public Health at Amazon
Web Services (AWS)

IDPH
Illinois Department of Public Health

Measles Outbreak Simulator Dashboard

Changing the response from reactive to proactive

Dejan Jovanov (he/him)

Chief Data and Informatics Officer

Illinois Department of Public Health

Setting the Stage:

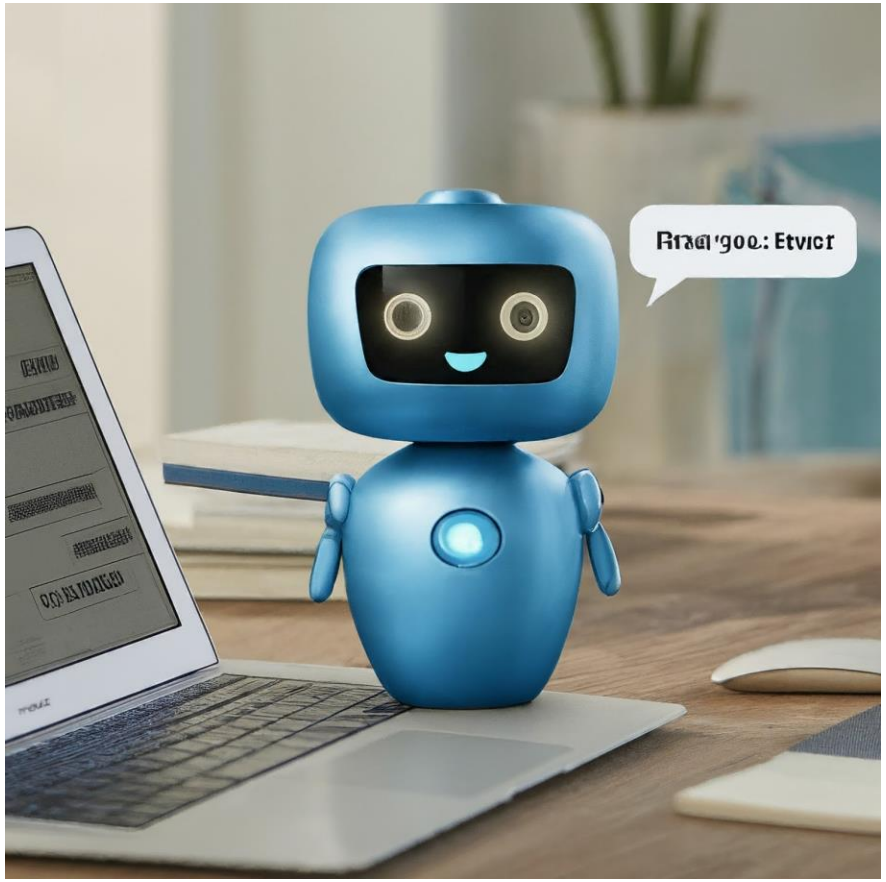
Purpose:

Projects and estimates the likelihood of measles outbreaks in Illinois schools (PreK–12) using:

- School vaccination rates
- Enrollment data
- Additional model parameters

- **Background:**
  - Released by the Illinois Department of Public Health (IDPH) in April 2025 due to a nationwide surge in measles cases
  - Inspired by the University of Texas Austin *epiEngage Measles Outbreak Simulator*
  - Part of our initiative to transform the IDPH data ecosystem from reactive to proactive

- **Use:**
  - Supports school administrators and staff in outbreak prevention and control efforts
  - Inform the public



Measles Simulator Dashboard Data Components

IDPH
Illinois Department of Public Health

Illinois State Board of Education (ISBE) School Immunization Data and Directory Information (PreK-12)*

- Measles Vaccination Coverage %
- Enrollment Counts

1 Basic Reproduction Number (R0)

- The average number of individuals in a susceptible population that become infected after exposure to an infectious individual with measles.

2 Average Latent Period (days)

- The number of days a person is infected with measles before they become infectious.

3 Average Infectious Period (days)

- The average number of days an individual with measles can continue to spread or infect others with measles.

4 Minimum Outbreak Size (new infections)

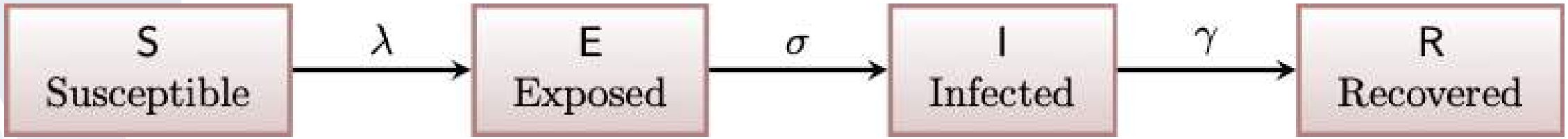
- The minimum number of new infections needed to define an outbreak in the selected school.

Likelihood and Size of a Measles Outbreak in an Illinois School

IDPH
Illinois Department of Public Health

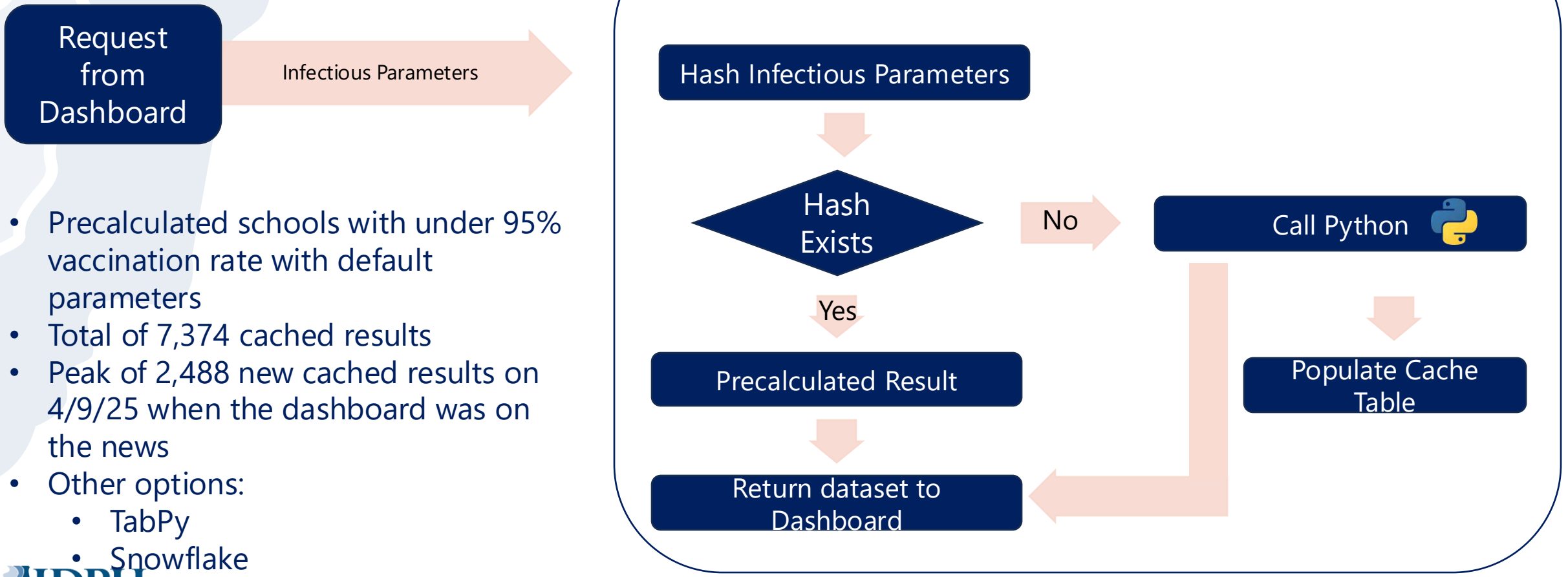
*School data included in the model and additional information can be found in the Illinois School Vaccination Coverage Dashboard.
Numbered model components above are preset, but dashboard users have the option of modifying values to alter the simulator model.

SEIR model used for Measles Prediction



- **Model Overview:**
- **SEIR** = *Susceptible → Exposed → Infected → Removed*
- Population moves between compartments based on defined rates.
- **Key Parameters:**
- **λ (Exposure Rate):** How quickly susceptible individuals become exposed
- **σ (Latent Rate):** How quickly exposed individuals become infected
- **γ (Removed Rate):** How quickly infected individuals recover or are removed
- Also includes: vaccine rate, initial infection, contact rate, basic reproduction number (**R_0**)
- Defaults follow CDC Measles Clinical Diagnosis Fact Sheet

Measles Simulator Dashboard Calculation Process



- Precalculated schools with under 95% vaccination rate with default parameters
- Total of 7,374 cached results
- Peak of 2,488 new cached results on 4/9/25 when the dashboard was on the news
- Other options:
  - TabPy
  - Snowflake

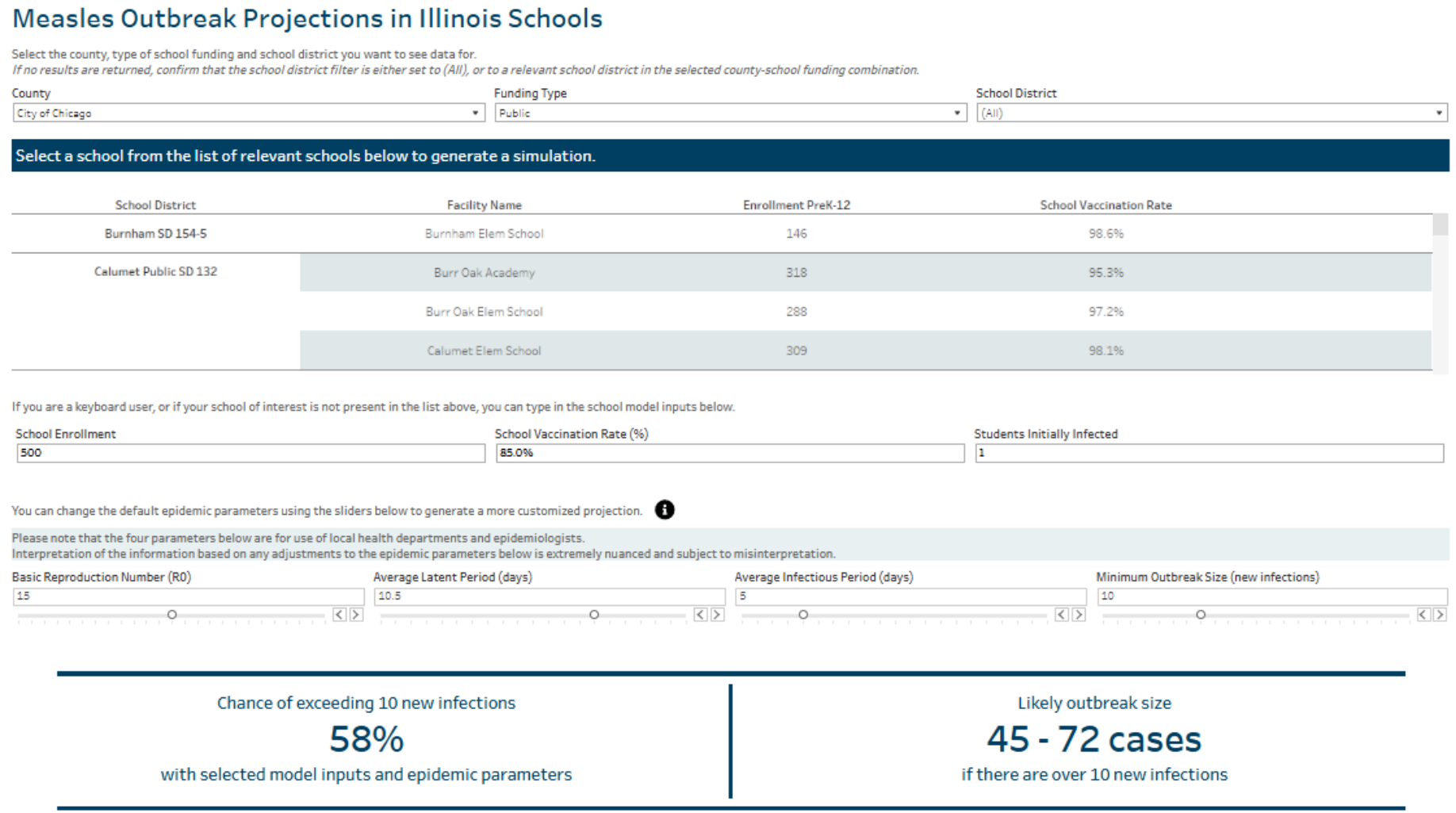
Measles Simulator Dashboard
Dashboard Parameters

1.Choose Enrollment & Vaccination Rates
•Select manually or pick a specific school.

2. Filter Schools
•Use County, Funding Type, and School District filters.
•If the county is changed, adjust the School District drop-down or set to (All).

3. Update & Select
•The table updates based on your selections.
•Click a school to use its enrollment and vaccination rate.
•Values can also be adjusted manually to model changes.

4. Adjust Epidemic Parameters
•Modify the minimum outbreak size to change the threshold for potential outbreaks.
•Other epidemic parameters can be updated for custom scenarios.

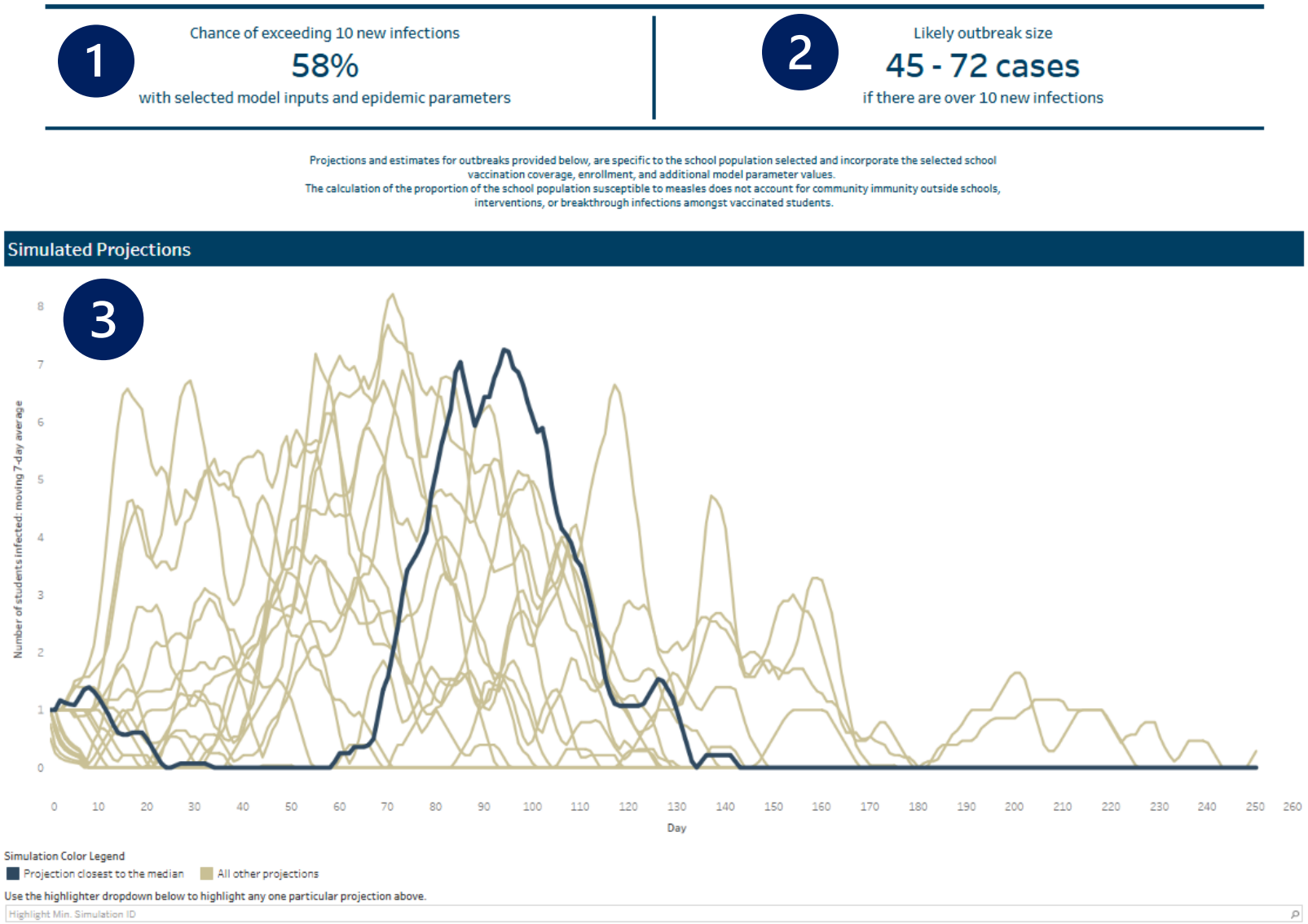


Measles Simulator Dashboard

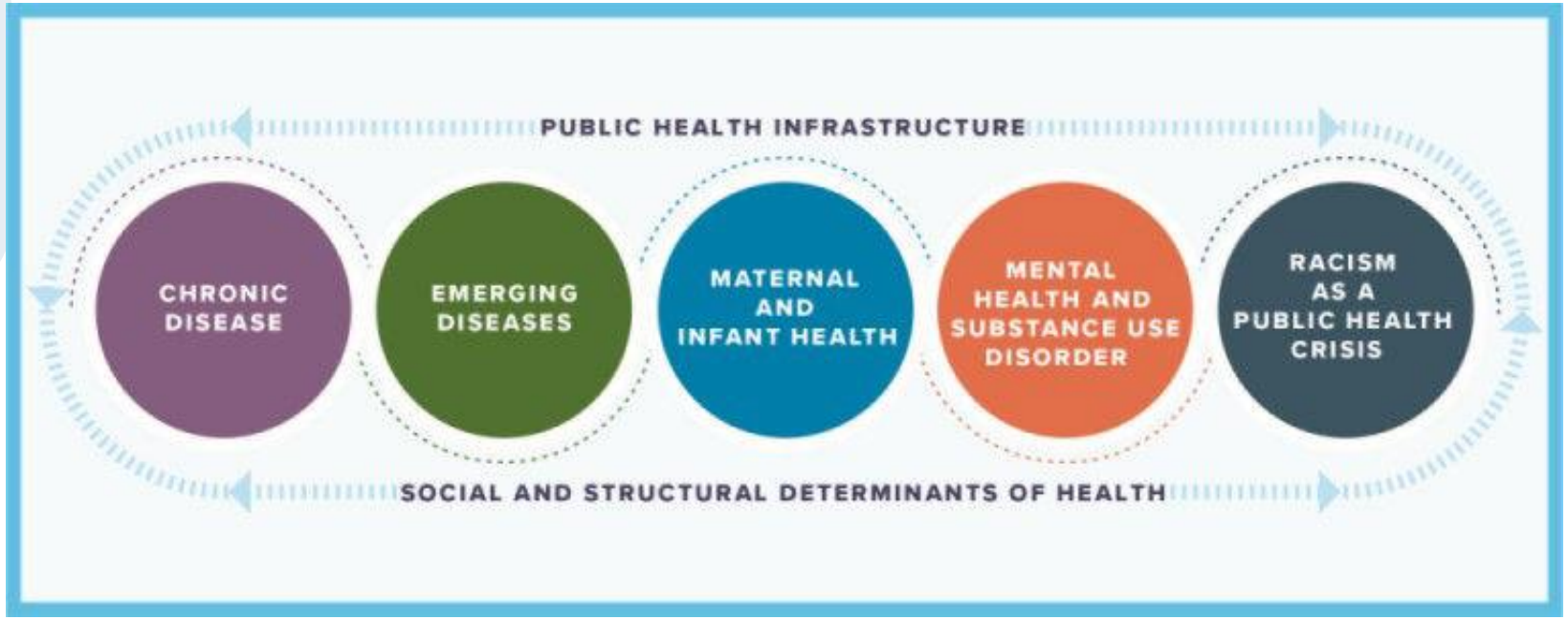
Dashboard Results

The results are calculated by running 200 stochastic simulations using the entered parameters.

1. The "Chance of exceeding X new infections" is the percentage of simulations that had more infections than the selected minimum (10 by default).
2. Likely outbreak size uses the middle 95% of the outbreaks that are larger than the selected minimum (10 by default).
3. The simulated projections show a random selection of 20 outbreak projections. The highlighted line is the projection with the outbreak size nearest to the median.



What's Next



- Adapt the SEIR model (adding compartments, age groups, vaccination status, seasonality) to fit the specific disease.
- Expand the use of the model on diseases with a clear incubation period (e.g., measles, COVID-19, influenza).
- Build additional dashboards

Questions?

Contact:

Dejan Jovanov: Dejan.Jovanov@Illinois.gov

IDPH
Illinois Department of Public Health

Project CLAIRE: Comprehensive Language Model Artificial Intelligence for Record Evaluation - Assessing the use of Artificial Intelligence for Infectious Disease Surveillance

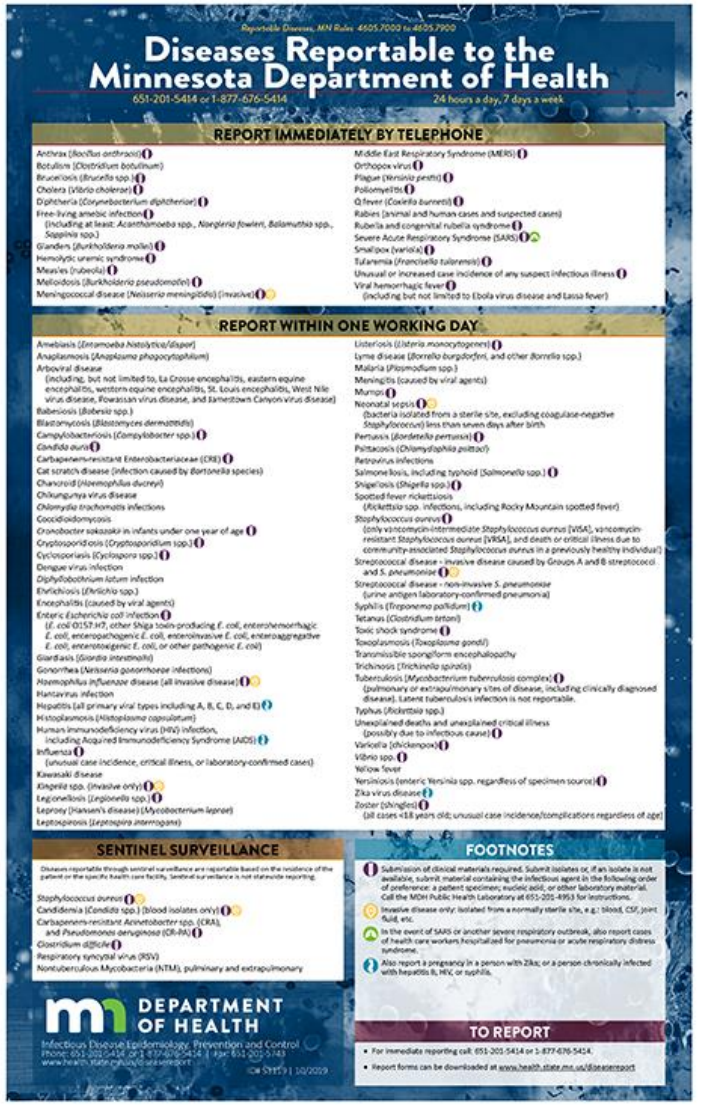
Stephanie Meyer, MPH

Epidemiology Supervisor | Infectious Disease Epidemiology, Prevention, and Control Division

Minnesota Department of Health

Background

- COVID-19 is one of many reportable diseases in Minnesota
- Minnesota is part of the CDC Emerging Infections Program
- Medical chart abstractions are often necessary
- COVID-NET monitors laboratory-confirmed, COVID-19-associated hospitalizations among children and adults



Diseases Reportable to the Minnesota Department of Health

651-201-5414 or 1-877-676-5414 — 24 hours a day, 7 days a week

REPORT IMMEDIATELY BY TELEPHONE

REPORT WITHIN ONE WORKING DAY

SENTINEL SURVEILLANCE

FOOTNOTES

TO REPORT

DEPARTMENT OF HEALTH

Infectious Disease Epidemiology, Prevention and Control

What is a Medical Chart Review?

ED Vitals:
Patient Vitals for the past 24 hrs:

	BP	Temp	Pulse	Resp	SpO2	Height	Weight
09/02/23 0202	127/85	99 °F (37.2 °C)	97	22	94 %	—	—
09/02/23 0000	**(!) 115/91**	—	**(!) 110**	**(!) 34**	95 %	—	—
09/01/23 2345	128/78	—	**(!) 103**	**(!) 32**	95 %	—	—
09/01/23 2330	—	—	**(!) 103**	**(!) 26**	95 %	—	—
09/01/23 2315	**(!) 128/116**	—	**(!) 108**	**(!) 32**	94 %	—	—
09/01/23 2306	136/88	99.5 °F (37.5 °C)	**(!) 107**	20	97 %	5' 4.02" (1.626 m)	84.8 kg

MDM:
[redacted] is a 76 y.o. female who presents for the above. The differential includes pneumonia, sepsis, viral syndrome, antibiotic reaction. The patient has generalized weakness here and recent diagnosis of pneumonia. Patient is given albuterol treatment. Sepsis protocol was started and she is given some lactated Ringer's. Patient is given levofloxacin after extensive conversation with her about her allergies and given the pneumonia. Chest x-ray does show significant left-sided infiltrate. She has significant hyponatremia as well. I did discuss the case with renal on-call who recommended fluid resuscitation and recheck of sodium. Patient is transferred to hospitalist service for further work-up and care.

DIAGNOSIS:

		ICD-10-CM
1.	**Pneumonia of left lung due to infectious organism, unspecified part of lung**	**J18.9**
2.	Hyponatremia	E87.1

Medical charts are read and reviewed to determine:

- Course of illness
- Course of hospitalization
- Treatments
- Underlying Conditions

10/01/2022 - ED to Hosp-Admission (Discharged) in W3 (continued)

l Notes (group 1 of 2) (continued)

g: Take 25 mg by mouth once daily.				
holecalciferol, vitamin D3, 25 mcg, 1000 nit, 25 mcg (1,000 unit) oral tablet g: Take 25 mcg by mouth once daily.	9/29/2022	Patient	Yes	Yes
yclobenzaprine (FLEXERIL) 10 mg oral blet g: Take 10 mg by mouth every evening.	9/29/2022	Patient	Yes	Yes
ulaglutide (TRULICITY) 1.5 mg/0.5 mL SubQ en g: Inject 1.5 mg under the skin every 7 (seven) days.	9/23/2022	Patient	Yes	Yes
abapentin (NEURONTIN) 300 mg oral apsule g: Take 300 mg by mouth three times a day.	9/29/2022	Patient	Yes	Yes
ipiZIDE (GLUCOTROL XL) 5 mg oral xtended release tablet 24 HR g: Take 5 mg by mouth twice a day.	9/29/2022	Patient	Yes	Yes
ultivit-mins/iron/folic/lycop (CENTRUM EN ORAL) g: Take 1 capsule by mouth once daily.	9/29/2022	Patient	Yes	Yes
aloxone (NARCAN) 4 mg/actuation Nasal pray g: Instill 4 mg into one nostril as needed. Seek emergency care immediately after use.	PRN	Patient	Yes	Yes
xyCODONE (OXYCONTIN) 20 mg oral xtended release tablet 12 HR g: Take 20 mg by mouth twice a day.	9/29/2022	Patient	Yes	Yes
xyCODONE, immediate release, ROXICODONE) 15 mg oral tablet g: Take 15 mg by mouth every 4 (four) hours as needed.	9/29/2022	Patient	Yes	Yes
antoprazole (PROTONIX) 40 mg oral elayed release tablet g: Take 40 mg by mouth once daily.	9/29/2022	Patient	Yes	Yes
varoxaban (XARELTO) 20 mg oral tablet g: Take 20 mg by mouth once daily.	9/30/2022 @0200	Patient	Yes	Yes
msulosin (FLOMAX) 0.4 mg oral capsule g: Take 0.4 mg by mouth at bedtime.	9/29/2022	Patient	Yes	Yes
aZODone (DESYREL) 100 mg oral tablet g: Take 100 mg by mouth at bedtime.	9/29/2022	Patient	Yes	Yes

Medical Chart Layout

- Medications or treatments may be listed over multiple pages or multiple days
- Each treatment may have been administered already or something that the patient will take home
- Details and nuance about dosage and timing can be very important in relation to an infection

Chart Abstractions

4. Height: 65 — in / cm — reset

5. Weight: 116.3 — lbs / kgs — reset

6. BMI (non-pregnant cases and cases 2+ years old): 42.7 (42.7) View equation

7. Smoker (tobacco): Current / Former / No/ Unknown — reset

7a. Smoker (marijuana/vaping) *[MN question]*: Current / Former / No/ Unknown — reset

Type of non-tobacco smoking (select all that apply):

8. Environmental tobacco smoke exposure (for pediatric patients ≤12years):

9. Alcohol misuse: Current / Former / No/ Unknown — reset

10. Substance misuse: Current / Former / No/Unknown — reset

11. Substance MisuseType (current use only) (Select all that apply):

- [ ] IVDU
- [x] Opioids
- [ ] Cocaine
- [ ] Methamphetamines
- [ ] Marijuana
- [ ] Polysubstance abuse - not otherwise specified
- [ ] Unknown
- [ ] Other, specify

12. Code status on admission:

- (•) Full code
- ( ) DNR (Do Not Resuscitate) / DNI (Do not Intubate) / CMO (Comfort measures only)
- ( ) Unknown

reset

ICU and Other interventions

Invasive mechanical ventilation? (•) Yes ( ) No ( ) Unknown — reset

BiPAP or CPAP? ( ) Yes (•) No ( ) Unknown — reset

High flow nasal cannula (e.g. Vapotherm)? ( ) Yes (•) No ( ) Unknown — reset

Supplemental Oxygen?

4. ECMO? ( ) Yes (•) No ( ) Unknown — reset

6. Renal Replacement Therapy (RRT) or Dialysis?

Includes Peritoneal Dialysis (PD), Hemodialysis (HD), Continuous Venovenous Hemofiltration (CVVH), Continuous Venovenous Hemodialysis (CVVHD), and Slow Continuous Ultrafiltration (SCUF)

( ) Yes (•) No ( ) Unknown — reset

7. Was the patient admitted to an intensive care unit (ICU)? (•) Yes ( ) No ( ) Unknown — reset

7a. Date of ICU admission: 12-24-2024 M-D-Y

7b. Date of ICU discharge: 12-25-2024 M-D-Y

F. Outcome

1. What was the outcome of the patient upon discharge?

- ( ) Alive
- (•) Died during hospitalization
- ( ) Unknown

reset

2. Date of death: 12-25-2024 M-D-Y

Medical Chart Review

- **Manual chart review involves multiple staff**
- **COVID-NET includes a sample of hospitalized cases for chart review**

Season*	2020-2021	2021-2022	2022-2023	2023-2024
Total COVID-NET Cases	39,318	34,154	14,908	12,971
Chart Reviews Completed	20,019 (50%)	7,006 (20%)	2,368 (16%)	2,669 (21%)
Review Staff	17	12	11	10

* Season starts October 1 through Sept 30 with exception of 2020-2021, which began in March 2020

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Chart Reviews Completed	20,019 (50%)	7,006 (20%)	2,368 (16%)	2,669 (21%)
Review Staff	17	12	11	10

- The cost of full-time staff to review thousands of charts is not tenable

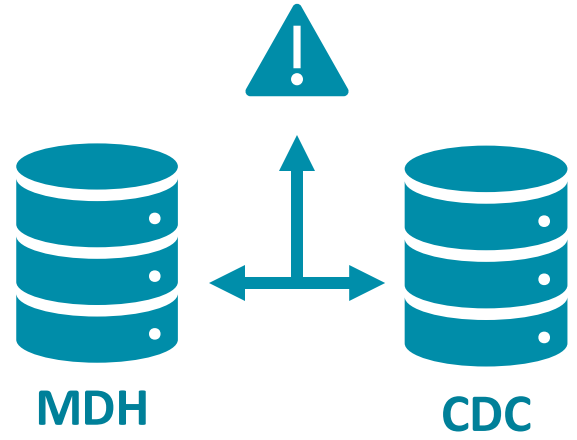
* Season starts October 1 through Sept 30 with exception of 2020-2021, which began in March 2020

Current State – Manual Process

Manual medical record review

- Up to 100 pages, 2-3 hours per record

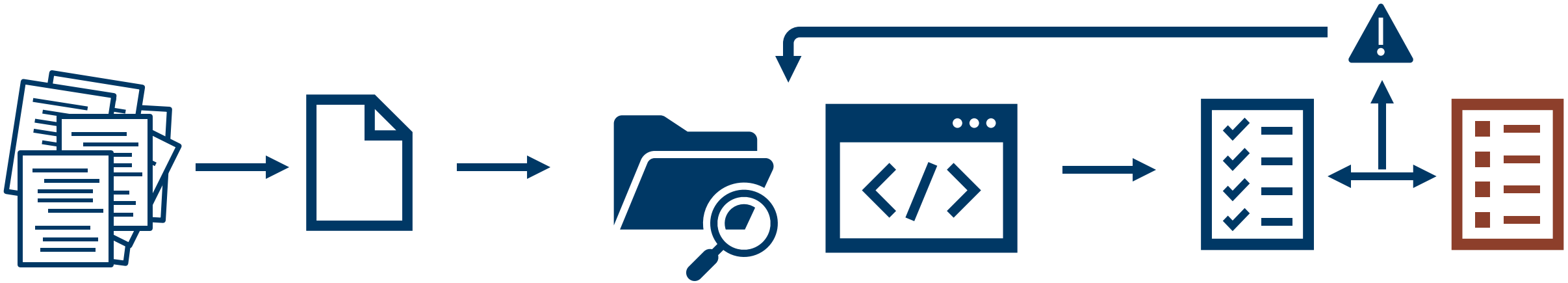
Manual medical record abstraction and data entry



Data sent from MDH to CDC, part of cooperative federal funding agreements

- If data entry errors are identified, problems are manually reviewed and re-abstracted

Future State



A document is generated with all the text from the medical record

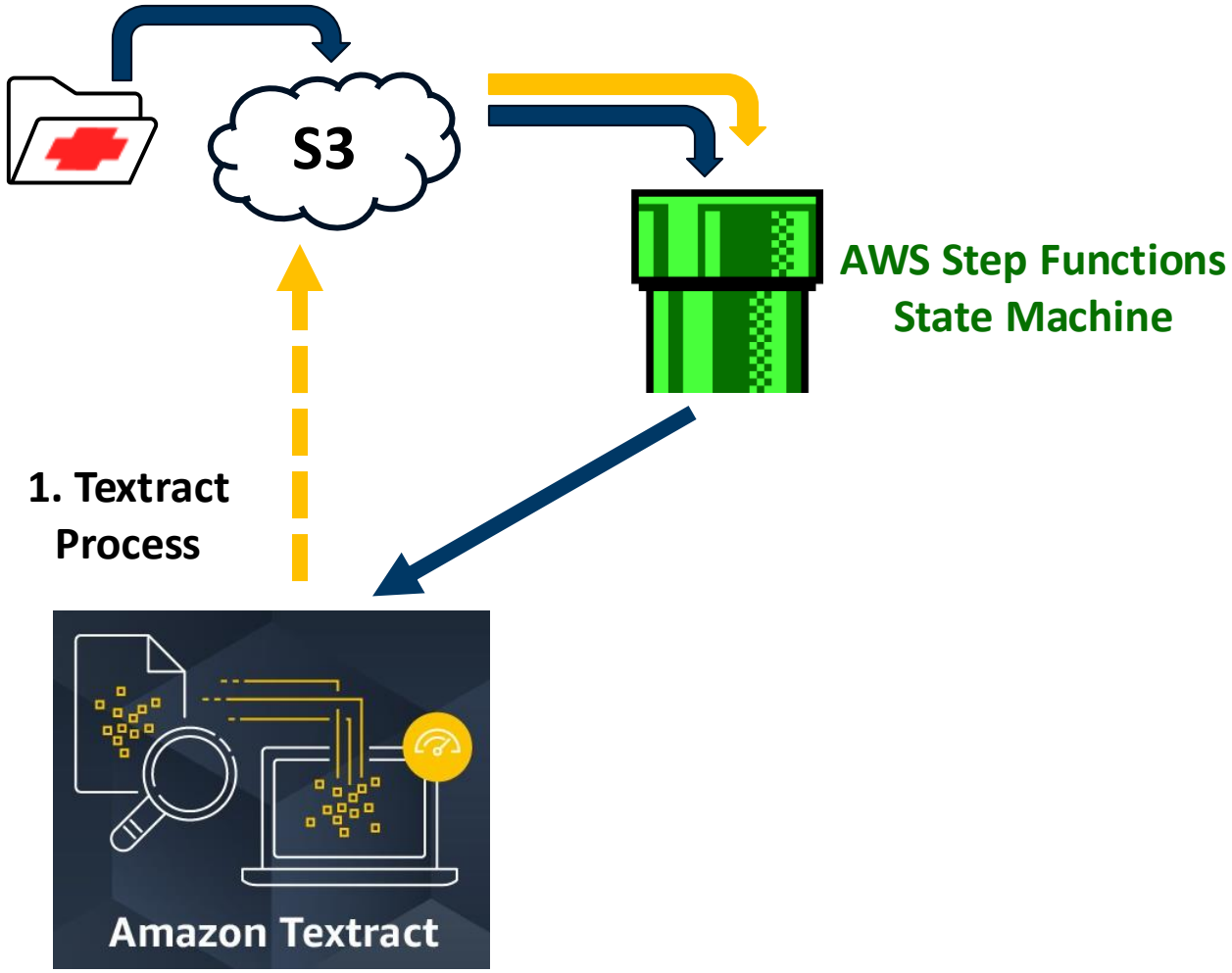
Use large language models to “read” the chart and extract key data elements
Includes code, prompt engineering, and large language model selection

Data is validated by comparison to manually collected data
Results are used to improve the abstraction pipeline

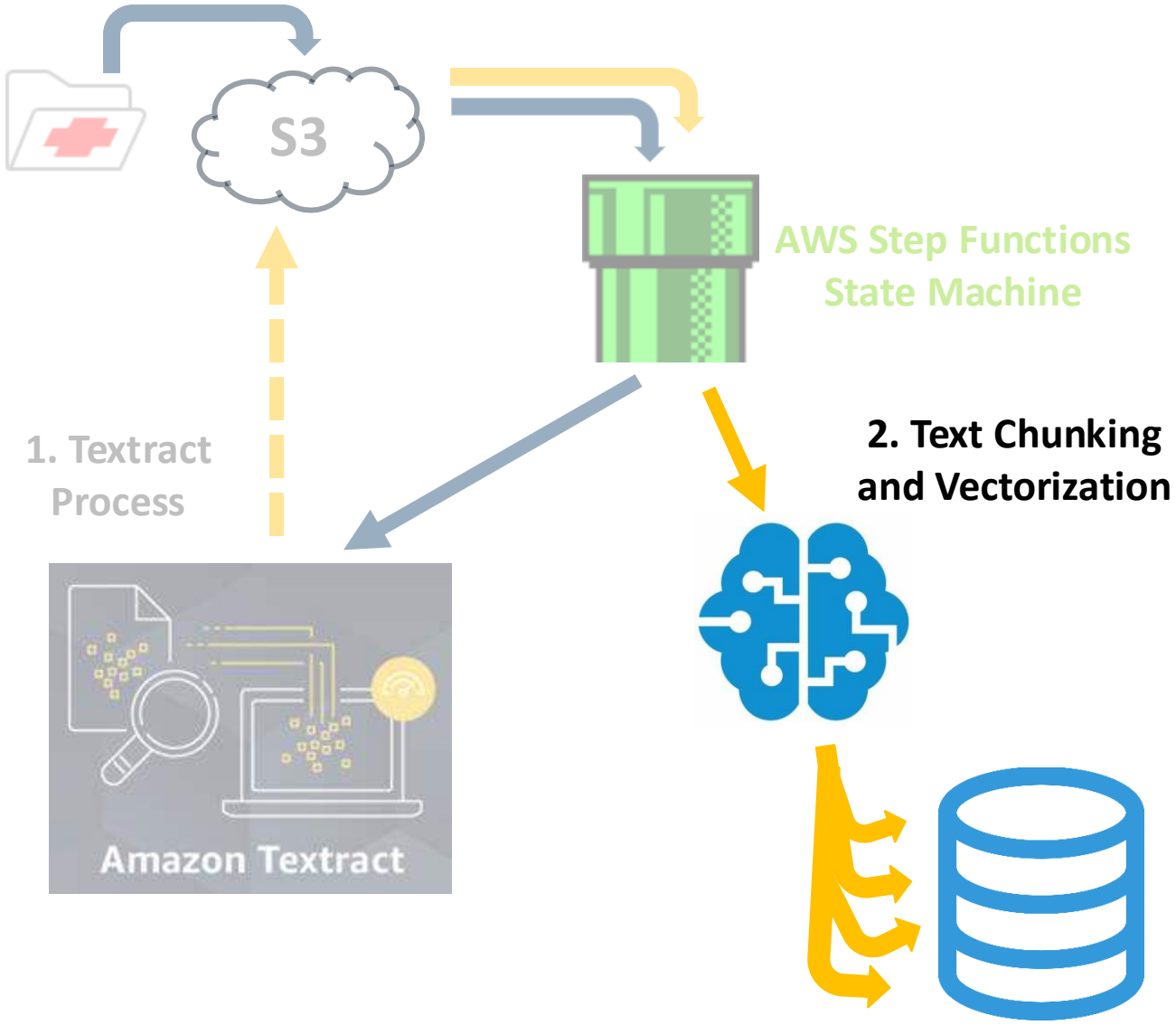
CLAIRE Pilot Project

- We identified 150 COVID-19 medical charts from one health system from the 2022-2023 respiratory season
- All charts were redacted PDF files
- All charts had been manually reviewed by Minnesota Department of Health (MDH) staff with answers entered into a REDCap database
- MDH partnered with MNIT MDH and Amazon Web Services (AWS) for evaluation of options
- Analysis of the results from text extracts of abstracted charts from the AWS pipeline were compared with manual abstractions

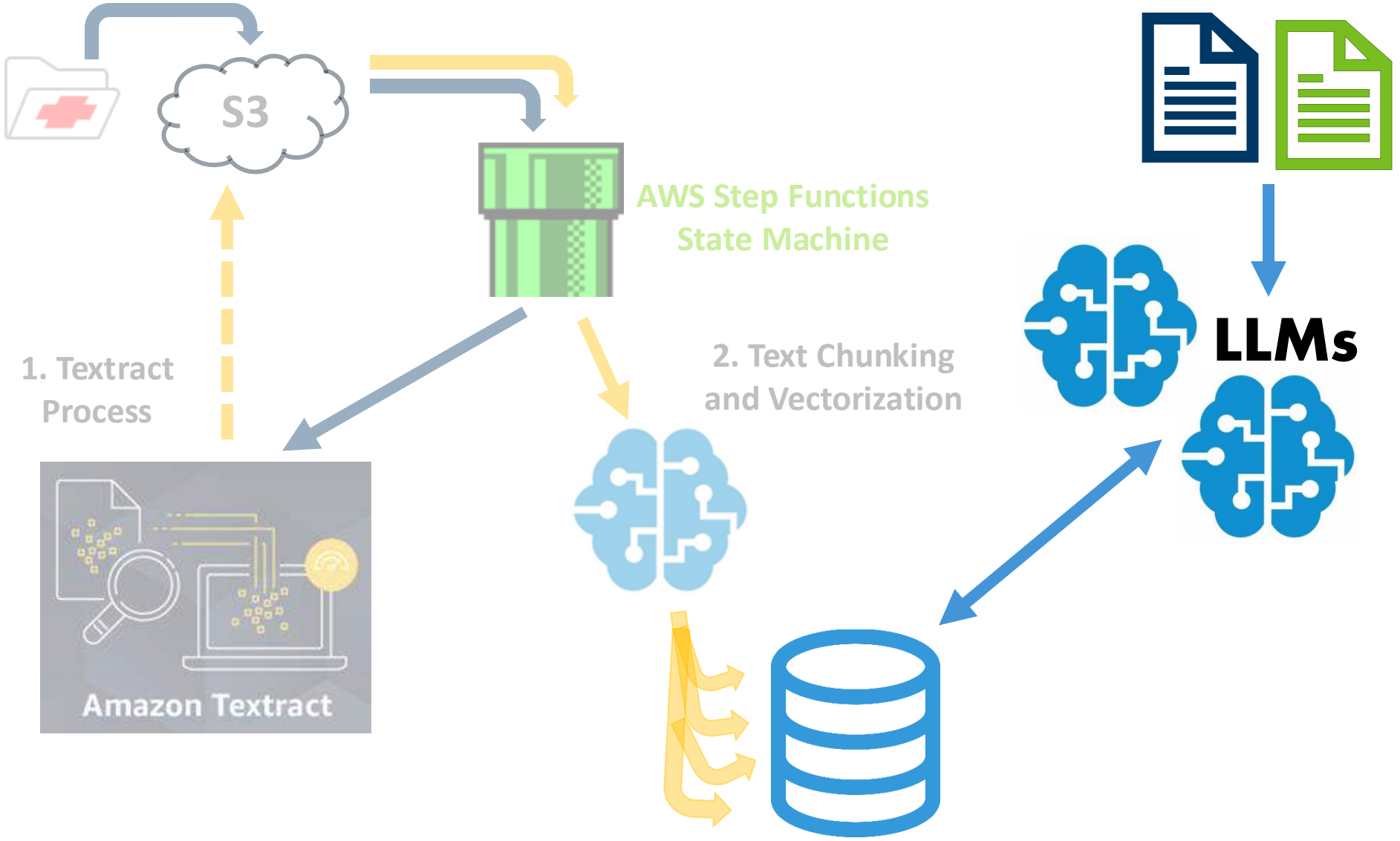
CLAIRE Pilot Project



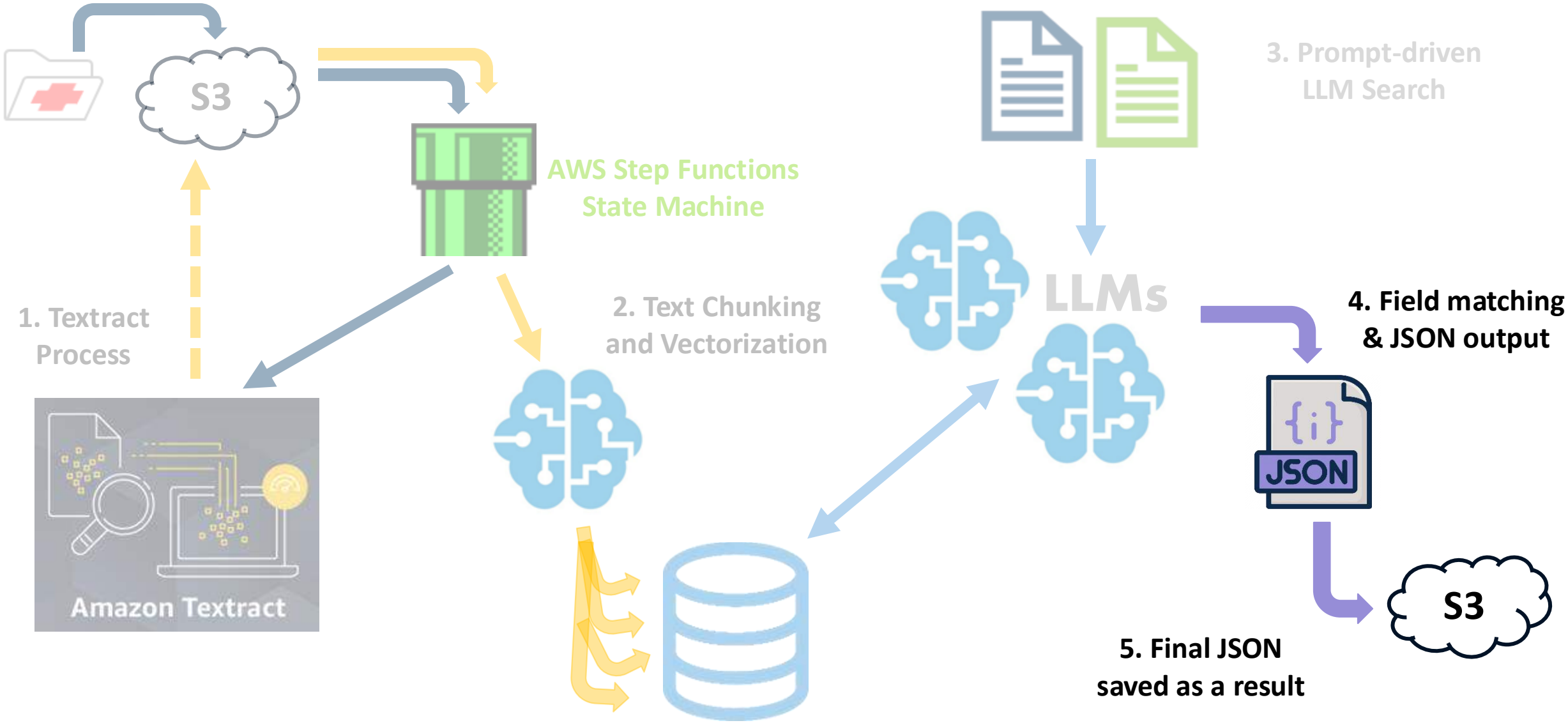
CLAIRE Pilot Project



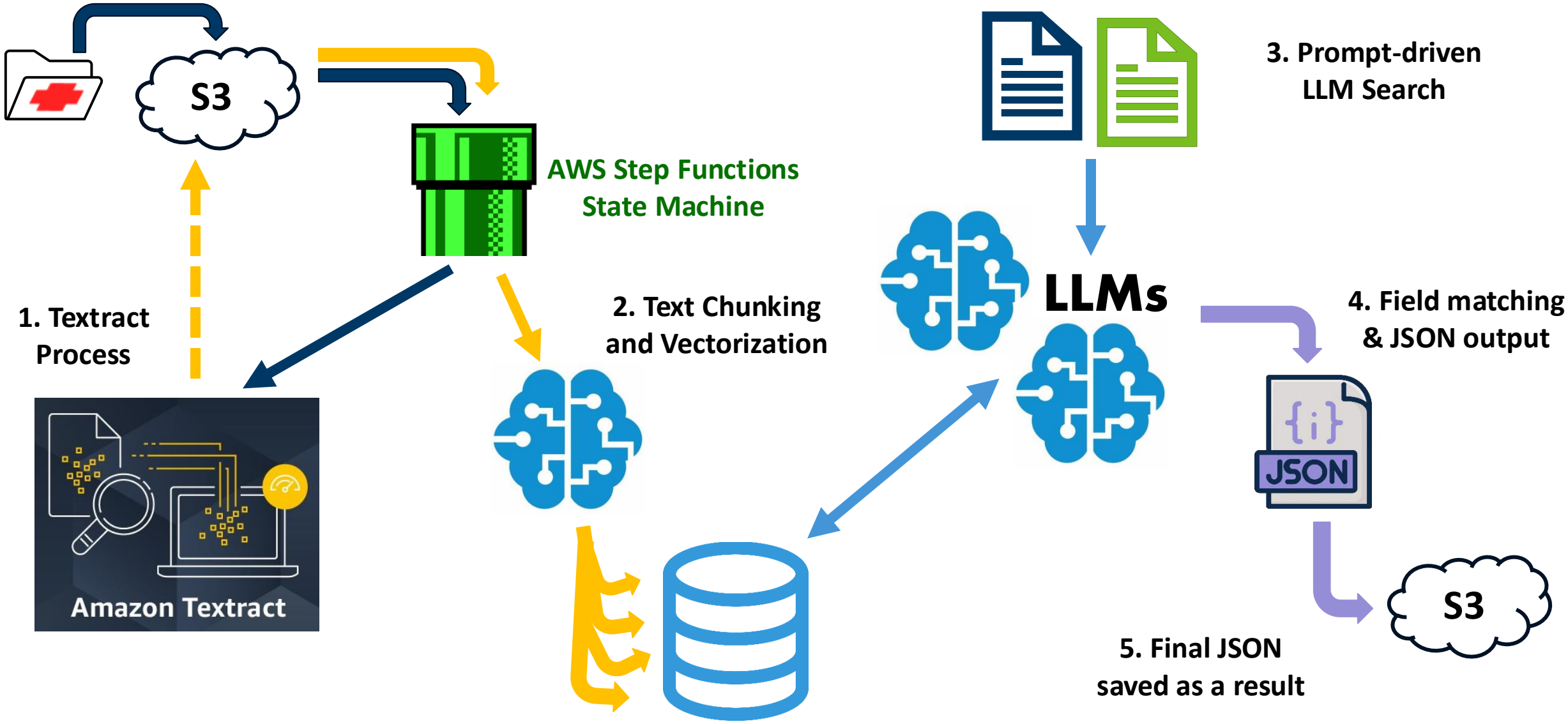
CLAIRE Pilot Project



CLAIRE Pilot Project



CLAIRE Pilot Project



Restructuring the Data

- Throughout the pilot project we looked at various data elements and corresponding accuracy
- We divided data into four categories:
- STRUCTURED DATA – data collection better suited to standard code
- PROMPT DRIVEN SEARCH – data collection that might require decision-making based upon additional information
- PROBABILISTIC MATCHING – data collection that we thought might be best-suited for LLMs
- SUMMARIZATION – data collection that might require manual review by staff, but a summary with citations could be helpful and streamline the work

Beneficial Early Results

- We looked at the accuracy by category

Category	Number of variables	Average accuracy across the category
STRUCTURED DATA	76	49.7%
PROMPT DRIVEN SEARCH	50	95.5%
PROBABILISTIC MATCHING	220	92.7%
SUMMARIZATION	33	88.1%

- STRUCTURED DATA variables had the lowest accuracy via large language model assessment
- SUMMARIZATION variables also had a lower accuracy score

Next Steps

- With adequate funding:
  - Continue CLAIRE pilot – more cases, more file types, more providers
  - Other medical chart reviews for other disease areas
  - eCR (Electronic Case Report) use
- Large language models (LLMs) combined with deterministic code may be a smart, hybrid approach to medical chart review, and could result in a more efficient use of staff time
- LLM use could expand our ability to use medical data directly from providers to better understand population health

Thank You!

This project was supported by Cooperative Agreements NU50CK000648-01-00 and NU50CK000508-05-02 from the Centers for Disease Control and Prevention.

Stephanie Meyer

stephanie.meyer@state.mn.us

Public Health Generative AI Use Cases

Agenda – Public Health Use Cases for GenAI

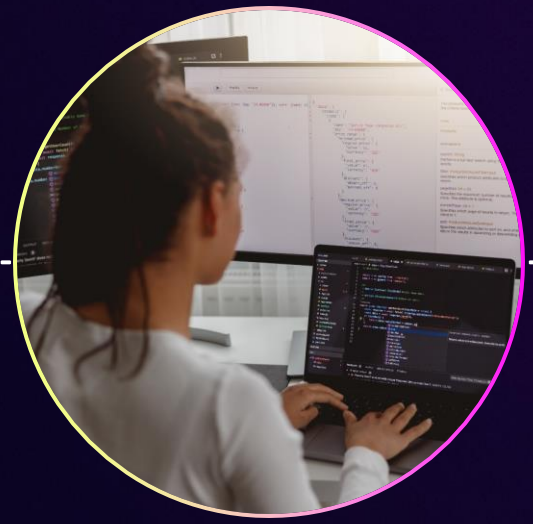
- Electronic Case Reports
- Intelligent Document Processing
- Chatbots
- Generative Business Intelligence and Data Analytics

Data Privacy & Security

Securely build generative AI applications with your data

Data is not used for service improvement

Data remains in the region where API is processed



Data is not shared with model providers

Data is always encrypted in transit and rest

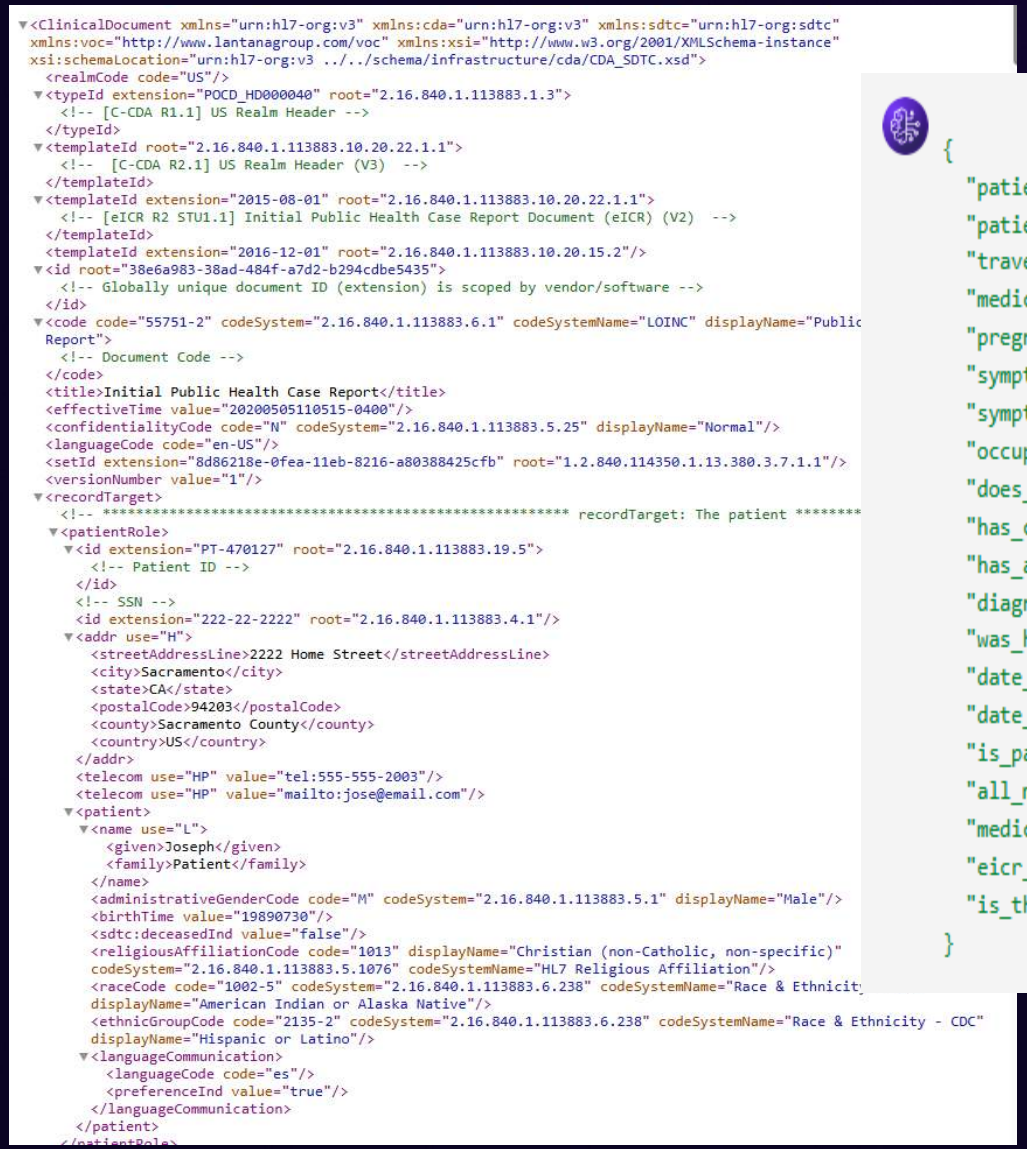
Build with comprehensive data protection & privacy;
leverage AWS security services and best practices

Electronic Case Reports

- Problem: Public Health receives thousands of large clinical documents (CDA and HL7) with actionable public health data buried in non-standard data elements, non-standard vocabularies and critical information in free text fields

- Solution: Use Generative AI to ask the questions that public health needs from electronic case reports and extract actionable public health data in a standard format
  - Pregnancy Status (Syphilis in a woman of child bearing age)
  - Occupation (Is the person with Hepatitis A food handler?)

Electronic Case Reports



```
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 xmlns:voc="http://www.lantanagroup.com/voc" xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
 xsi:schemaLocation="urn:hl7-org:v3 ../../schema/infrastructure/cda/CDA_SDTC.xsd">
  <realmCode code="US"/>
  <typeId extension="POCD_HD000040" root="2.16.840.1.113883.1.3">
    <!-- [C-CDA R1.1] US Realm Header -->
  </typeId>
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        <country>US</country>
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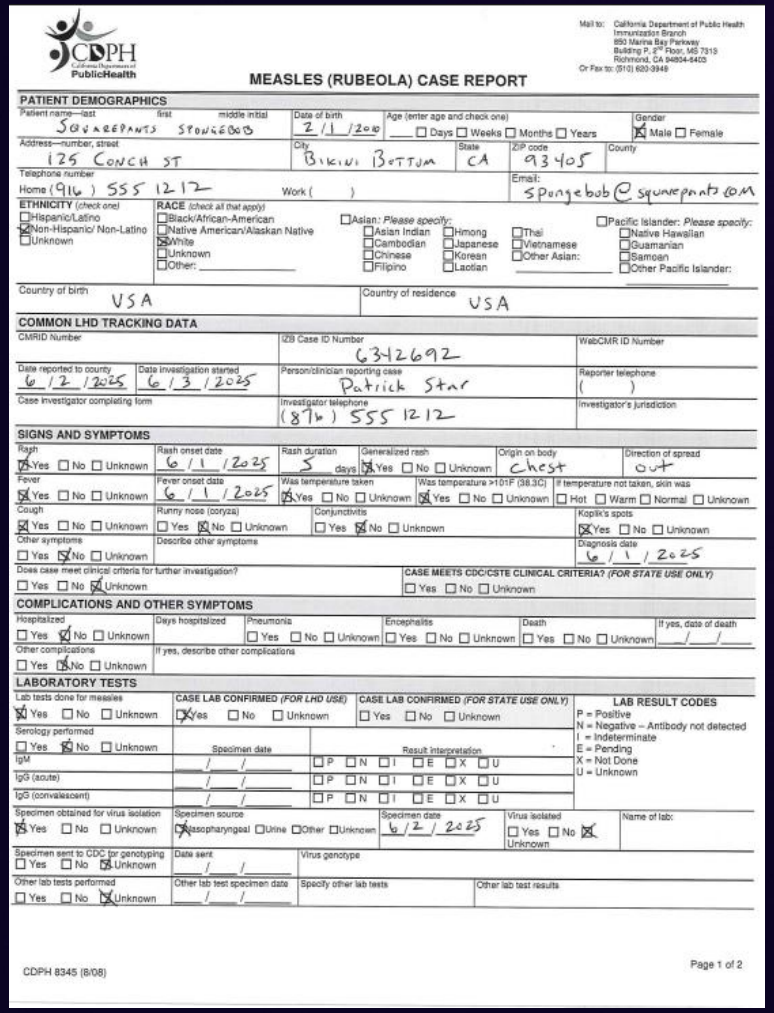
Intelligent Document Processing

- Problem: Public Health receives paper forms across multiple domains including Vital Records, Electronic Laboratory Reports, Communicable Disease Reports, and WIC applications

- Solution: Use Generative AI to automatically extract the data from paper forms and transform it into formats easily consumable by the systems of record.

Intelligent Document Processing



CDPH California Department of Public Health PublicHealth

Mail to: California Department of Public Health, Immunization Branch, 850 Marina Bay Parkway, Building P, 2nd Floor, MS 7319, Richmond, CA 94804-6403. Or Fax to: (510) 620-3948

MEASLES (RUBEOLA) CASE REPORT

PATIENT DEMOGRAPHICS

Patient name—last: SQUAREPANTS; first: SPONGEBOB; middle initial:
Date of birth: 2/1/200
Age (enter age and check one): ___ ☐ Days ☐ Weeks ☐ Months ☐ Years
Gender: ☒ Male ☐ Female
Address—number, street: 125 CONCH ST
City: BIKINI BOTTOM
State: CA
ZIP code: 93405
County:
Telephone number: Home (916) 555 1212 Work ( )
Email: Spongebob@squarepants.com

ETHNICITY (check one): ☐ Hispanic/Latino ☒ Non-Hispanic/ Non-Latino ☐ Unknown

RACE (check all that apply): ☐ Black/African-American ☐ Native American/Alaskan Native ☒ White ☐ Unknown ☐ Other: ___
☐ Asian: Please specify: ☐ Asian Indian ☐ Cambodian ☐ Chinese ☐ Filipino ☐ Hmong ☐ Japanese ☐ Korean ☐ Laotian ☐ Thai ☐ Vietnamese ☐ Other Asian: ___
☐ Pacific Islander: Please specify: ☐ Native Hawaiian ☐ Guamanian ☐ Samoan ☐ Other Pacific Islander: ___

Country of birth: USA
Country of residence: USA

COMMON LHD TRACKING DATA

CMRID Number:
IZIS Case ID Number: 6342692
WebCMR ID Number:
Date reported to county: 6/2/2025
Date investigation started: 6/3/2025
Person/clinician reporting case: Patrick Star
Reporter telephone: ( )
Case investigator completing form:
Investigator telephone: (874) 555 1212
Investigator's jurisdiction:

SIGNS AND SYMPTOMS

Rash: ☒ Yes ☐ No ☐ Unknown	Rash onset date: 6/1/2025	Rash duration: 5 days	Generalized rash: ☒ Yes ☐ No ☐ Unknown	Origin on body: chest	Direction of spread: out	
Fever: ☒ Yes ☐ No ☐ Unknown	Fever onset date: 6/1/2025	Was temperature taken: ☒ Yes ☐ No ☐ Unknown	Was temperature >101F (38.3C): ☒ Yes ☐ No ☐ Unknown	If temperature not taken, skin was: ☐ Hot ☐ Warm ☐ Normal ☐ Unknown		
Cough: ☒ Yes ☐ No ☐ Unknown	Runny nose (coryza): ☐ Yes ☒ No ☐ Unknown	Conjunctivitis: ☐ Yes ☒ No ☐ Unknown	Koplik's spots: ☒ Yes ☐ No ☐ Unknown			
Other symptoms: ☐ Yes ☒ No ☐ Unknown	Describe other symptoms:	Diagnosis date: 6/1/2025				
Does case meet clinical criteria for further investigation? ☐ Yes ☐ No ☒ Unknown	CASE MEETS CDC/CSTE CLINICAL CRITERIA? (FOR STATE USE ONLY) ☐ Yes ☐ No ☐ Unknown					

COMPLICATIONS AND OTHER SYMPTOMS

Hospitalized: ☐ Yes ☒ No ☐ Unknown	Days hospitalized:	Pneumonia: ☐ Yes ☐ No ☐ Unknown	Encephalitis: ☐ Yes ☐ No ☐ Unknown	Death: ☐ Yes ☐ No ☐ Unknown	If yes, date of death: ___/___/___
Other complications: ☐ Yes ☒ No ☐ Unknown	If yes, describe other complications:				

LABORATORY TESTS

Lab tests done for measles: ☒ Yes ☐ No ☐ Unknown
CASE LAB CONFIRMED (FOR LHD USE): ☒ Yes ☐ No ☐ Unknown
CASE LAB CONFIRMED (FOR STATE USE ONLY): ☐ Yes ☐ No ☐ Unknown

LAB RESULT CODES: P = Positive; N = Negative – Antibody not detected; I = Indeterminate; E = Pending; X = Not Done; U = Unknown

Serology performed: ☐ Yes ☒ No ☐ Unknown

	Specimen date	Result interpretation
IgM	___/___/___	☐P ☐N ☐I ☐E ☐X ☐U
IgG (acute)	___/___/___	☐P ☐N ☐I ☐E ☐X ☐U
IgG (convalescent)	___/___/___	☐P ☐N ☐I ☐E ☐X ☐U

Specimen obtained for virus isolation: ☒ Yes ☐ No ☐ Unknown
Specimen source: ☒ Nasopharyngeal ☐ Urine ☐ Other ☐ Unknown
Specimen date: 6/2/2025
Virus isolated: ☐ Yes ☐ No ☒ Unknown
Name of lab:
Specimen sent to CDC for genotyping: ☐ Yes ☐ No ☒ Unknown
Date sent: ___/___/___
Virus genotype:
Other lab tests performed: ☐ Yes ☐ No ☒ Unknown
Other lab test specimen date: ___/___/___
Specify other lab tests:
Other lab test results:

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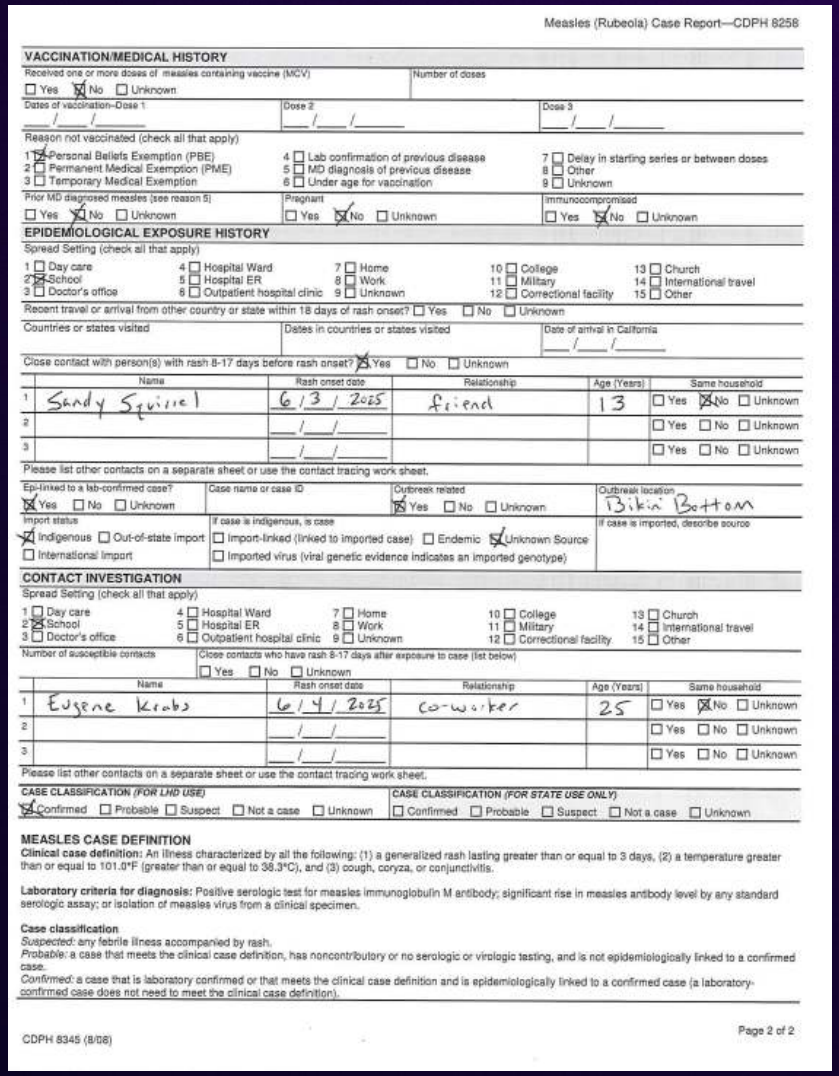

Measles (Rubeola) Case Report—CDPH 8258

VACCINATION/MEDICAL HISTORY

Received one or more doses of measles containing vaccine (MCV): ☐ Yes ☒ No ☐ Unknown
Number of doses:
Dates of vaccination–Dose 1: ___/___/___
Dose 2: ___/___/___
Dose 3: ___/___/___

Reason not vaccinated (check all that apply)
1 ☒ Personal Beliefs Exemption (PBE)
2 ☐ Permanent Medical Exemption (PME)
3 ☐ Temporary Medical Exemption
4 ☐ Lab confirmation of previous disease
5 ☐ MD diagnosis of previous disease
6 ☐ Under age for vaccination
7 ☐ Delay in starting series or between doses
8 ☐ Other
9 ☐ Unknown

Prior MD diagnosed measles (see reason 5): ☐ Yes ☒ No ☐ Unknown
Pregnant: ☐ Yes ☒ No ☐ Unknown
Immunocompromised: ☐ Yes ☒ No ☐ Unknown

EPIDEMIOLOGICAL EXPOSURE HISTORY

Spread Setting (check all that apply)
1 ☐ Day care
2 ☒ School
3 ☐ Doctor's office
4 ☐ Hospital Ward
5 ☐ Hospital ER
6 ☐ Outpatient hospital clinic
7 ☐ Home
8 ☐ Work
9 ☐ Unknown
10 ☐ College
11 ☐ Military
12 ☐ Correctional facility
13 ☐ Church
14 ☐ International travel
15 ☐ Other

Recent travel or arrival from other country or state within 18 days of rash onset? ☐ Yes ☐ No ☐ Unknown
Countries or states visited:
Dates in countries or states visited:
Date of arrival in California: ___/___/___

Close contact with person(s) with rash 8-17 days before rash onset? ☒ Yes ☐ No ☐ Unknown

	Name	Rash onset date	Relationship	Age (Years)	Same household
1	Sandy Squirrel	6/3/2025	friend	13	☐ Yes ☒ No ☐ Unknown
2		___/___/___			☐ Yes ☐ No ☐ Unknown
3		___/___/___			☐ Yes ☐ No ☐ Unknown

Please list other contacts on a separate sheet or use the contact tracing work sheet.

Epi-linked to a lab-confirmed case? ☒ Yes ☐ No ☐ Unknown
Case name or case ID:
Outbreak related: ☒ Yes ☐ No ☐ Unknown
Outbreak location: Bikini Bottom
Import status: ☒ Indigenous ☐ Out-of-state import ☐ International import
If case is indigenous, is case: ☐ Import-linked (linked to imported case) ☐ Endemic ☒ Unknown Source ☐ Imported virus (viral genetic evidence indicates an imported genotype)
If case is imported, describe source:

CONTACT INVESTIGATION

Spread Setting (check all that apply)
1 ☐ Day care
2 ☒ School
3 ☐ Doctor's office
4 ☐ Hospital Ward
5 ☐ Hospital ER
6 ☐ Outpatient hospital clinic
7 ☐ Home
8 ☐ Work
9 ☐ Unknown
10 ☐ College
11 ☐ Military
12 ☐ Correctional facility
13 ☐ Church
14 ☐ International travel
15 ☐ Other

Number of susceptible contacts:
Close contacts who have rash 8-17 days after exposure to case (list below): ☐ Yes ☐ No ☐ Unknown

	Name	Rash onset date	Relationship	Age (Years)	Same household
1	Eugene Krabs	6/4/2025	co-worker	25	☐ Yes ☒ No ☐ Unknown
2		___/___/___			☐ Yes ☐ No ☐ Unknown
3		___/___/___			☐ Yes ☐ No ☐ Unknown

Please list other contacts on a separate sheet or use the contact tracing work sheet.

CASE CLASSIFICATION (FOR LHD USE): ☒ Confirmed ☐ Probable ☐ Suspect ☐ Not a case ☐ Unknown
CASE CLASSIFICATION (FOR STATE USE ONLY): ☐ Confirmed ☐ Probable ☐ Suspect ☐ Not a case ☐ Unknown

MEASLES CASE DEFINITION

Clinical case definition: An illness characterized by all the following: (1) a generalized rash lasting greater than or equal to 3 days, (2) a temperature greater than or equal to 101.0°F (greater than or equal to 38.3°C), and (3) cough, coryza, or conjunctivitis.

Laboratory criteria for diagnosis: Positive serologic test for measles immunoglobulin M antibody; significant rise in measles antibody level by any standard serologic assay; or isolation of measles virus from a clinical specimen.

Case classification
Suspected: any febrile illness accompanied by rash.
Probable: a case that meets the clinical case definition, has noncontributory or no serologic or virologic testing, and is not epidemiologically linked to a confirmed case.
Confirmed: a case that is laboratory confirmed or that meets the clinical case definition and is epidemiologically linked to a confirmed case (a laboratory-confirmed case does not need to meet the clinical case definition).

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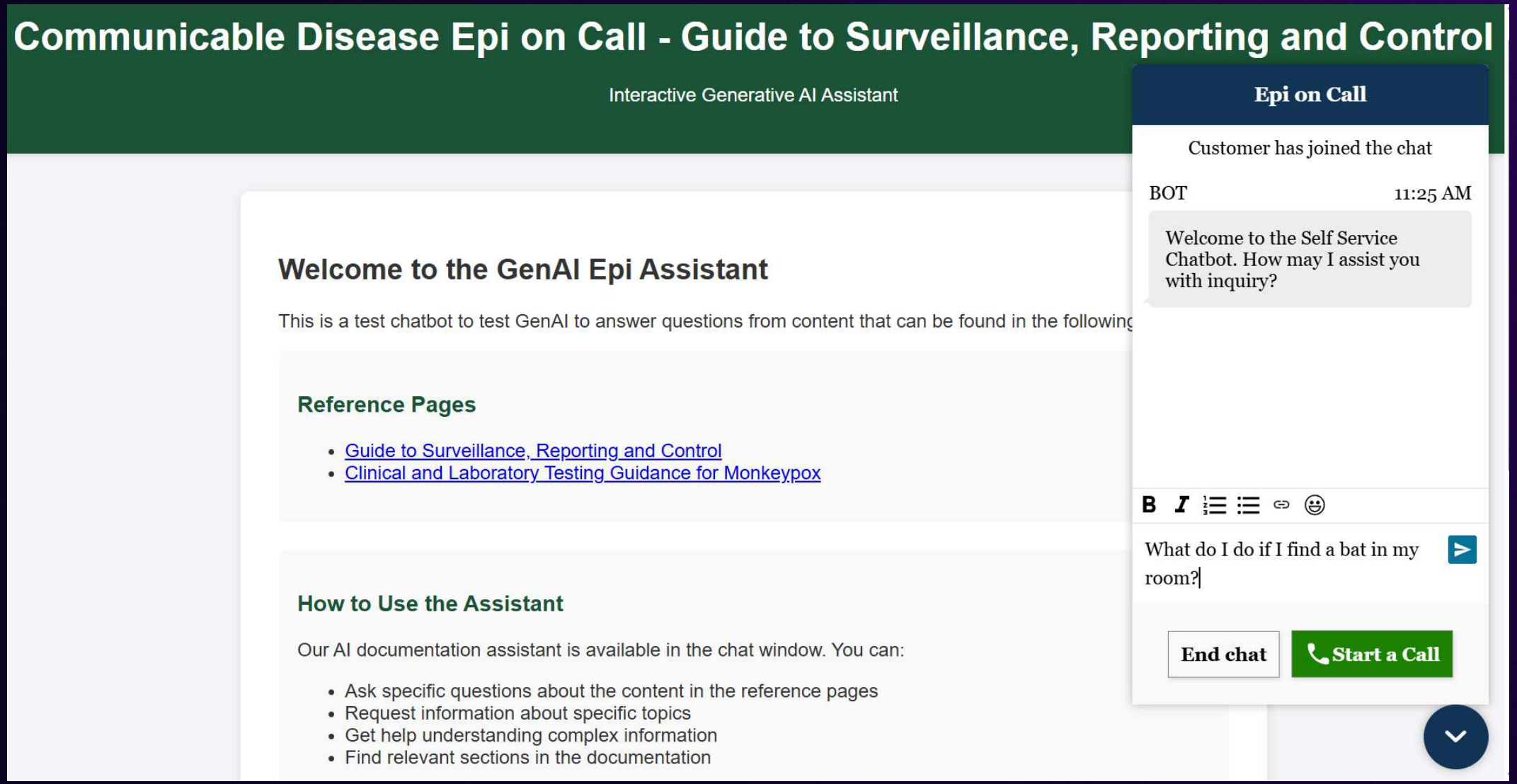
Generative AI Chatbots

- Problem: Public Health departments receive multiple inquiries. Providers using Vital Records and Immunization Information Systems call asking basic questions about how to use these systems. The general public may also call Public Health with simple questions about how to obtain an immunization record or how to enroll in a program like WIC. Although this information is on the Public Health

- Solution: Using Generative AI, resources from public health like user manuals and public facing websites can be the knowledge bases to enable chatbots to automatically answer questions from end users and the general public.

AI Chatbots



Generative Business Intelligence

- Problem: Public Health staff do not always have the technical and analytic skills to interact with their data to generate the graphs and stories from their siloed systems to help improve population health.

- Solution: Generative BI enables business users to interact with their data using natural language prompts to build graphs, dashboards and stories that describe their data

AI-assisted storytelling

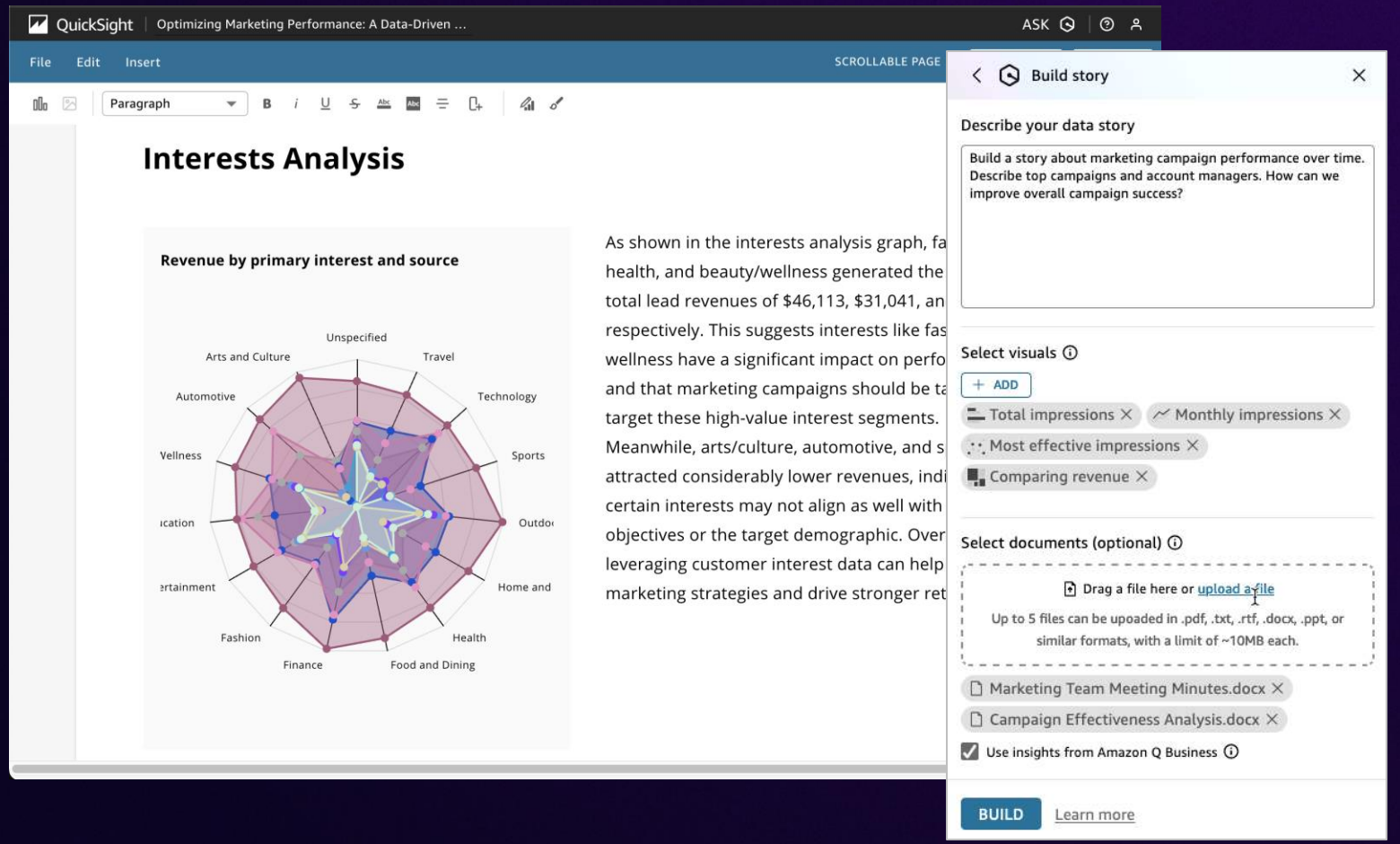
Interpret data for others
Help others derive meaning from data and reach conclusions to drive decisions

Generate stories using AI
Produce cohesive, powerful, and insightful narratives

Create refined content
Control AI verbosity, customize narrative text, and apply stunning visual themes to bring content to life

Augment with unstructured data
Upload files with related content to enrich the story with additional insights

Share up-to-date governed data
Quickly update and disseminate data at any time

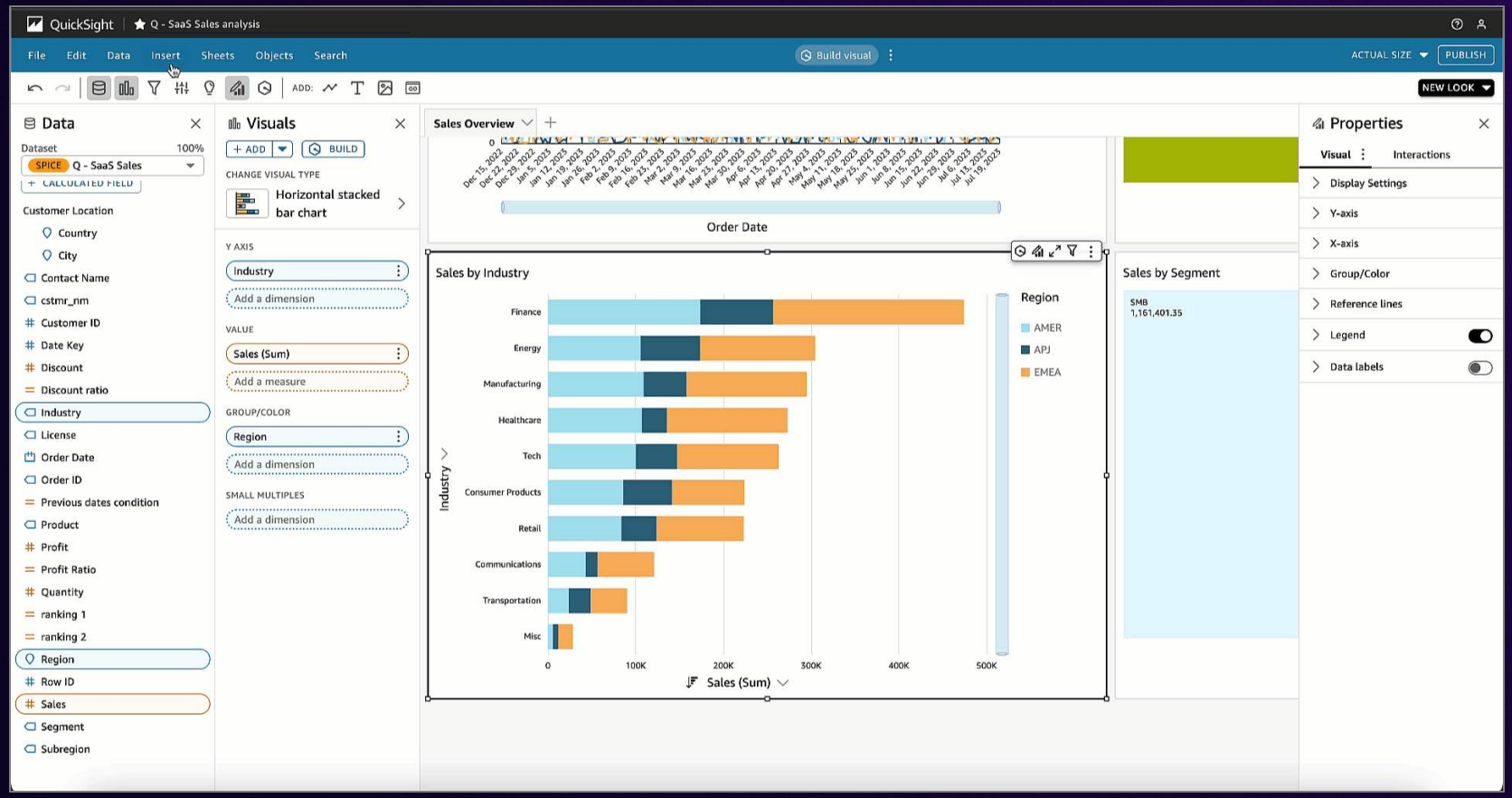


Generative Business Intelligence

Build visuals
Use natural language
to quickly build visuals for
dashboards and reports

Build calculations
Easily create calculations using
natural language without looking
up or learning specific syntax

Refine visuals
Quickly update visuals by
describing desired formats
using natural language



Blog: Transforming electronic case reporting with generative AI: Unlocking faster public health responses

Blog: Scalable intelligent document processing using Amazon Bedrock

Thank you!

PHIG PARTNERS

Audience Q & A

PHIG PARTNERS

Thank You!

UP NEXT…

5-6pm Central Time | Join us for our ***Data Modernization in Motion Networking Reception*** – Park View, 4th Floor

TOMORROW…

8:30-9:30am Central Time | Hashbrowns & High Tech Peer Networking Breakfast

9:45am Central Time | Concurrent sessions continue, followed by preconference closing plenary