

Predictive Modeling and Analysis of Adverse Events Post-Shingles Vaccination

: Serious Adverse Event Prediction Model Development &
Data Analysis Using VAERS Dataset

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Faculty Academic Mentor: Dr. Peter McGarvey (Director, ICBI Georgetown University)

Opinion | Vaccine hesitancy is growing. Doctors will have to fight back.

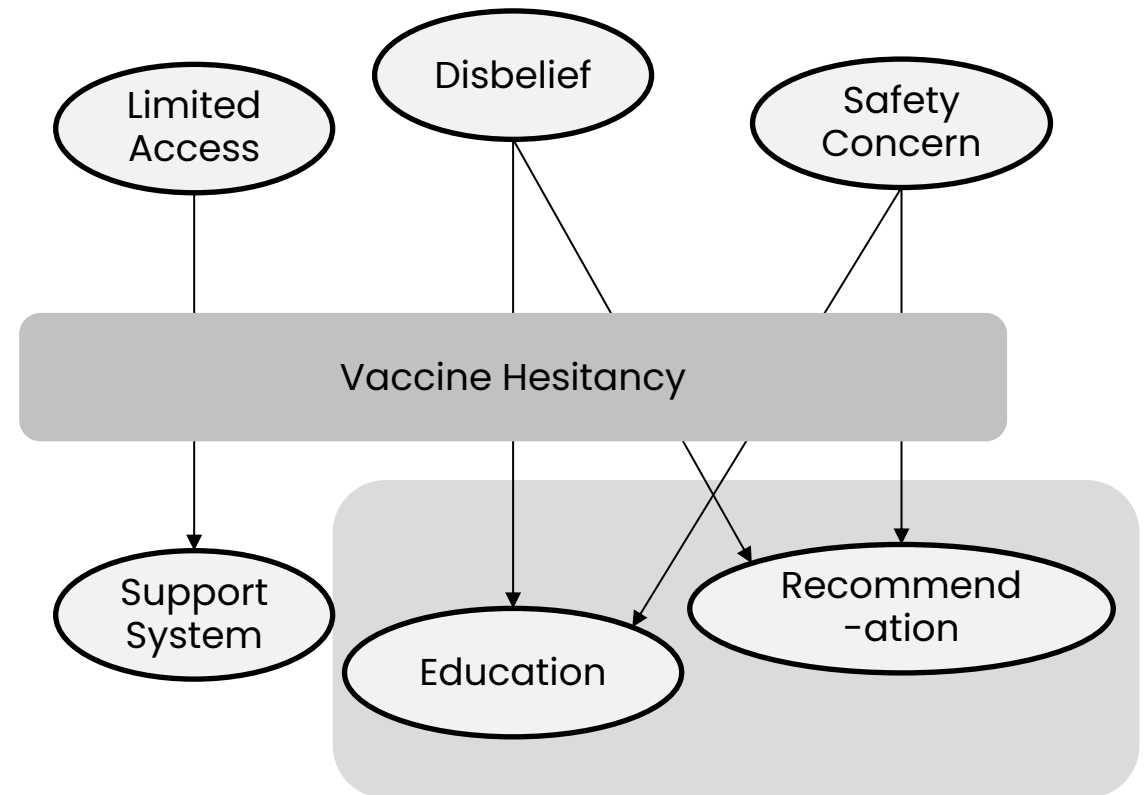


A nurse prepares a coronavirus vaccine dose at the Ward 4 D.C. Covid Center on March 31. (Eric Lee for The Washington Post)



By the Editorial Board

May 17, 2023 at 4:53 p.m. EDT



PROJECT INTRODUCTION

Problem

- Concerns of potential adverse events may lead to hesitancy among potential recipients.
- Shingles vaccines are not mandatory, so individual decision-making is important.

Scope

- Develop SAE (after AE onset) prediction model using VAERS data.
- Conduct statistical analysis of subgroups.

Goal

- Target AUPRC improvement of 20% (vs baseline model).
- Identify groups with higher risks.

Benefits

- Early intervention can lead to better patient care outcomes and potentially reduce healthcare costs.
- Patients and healthcare professionals can make more confident and informed decisions.

Timeline

May 2024 –
August 2024

Method

- Python
- R
- NLP
- Machine Learning
- Statistical Analysis

Sponsor



Industry Mentor

Dr. Azade Tabie, Data Scientist, MedStar Health

Academic Mentor

Dr. Peter McGarvey, Director, ICBI, Georgetown University

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01 INTRODUCTION



SHINGLES & VACCINATION



What is Shingles?

- Caused by reactivation of dormant Varicella-Zoster Virus.
- 1/3 people in US will have shingles in their lifetime.
- Postherpetic neuralgia (PHN).



Shingles Vaccine

- Recombinant Shingles Vaccine approved by FDA in 2017 (Shingrix).
- Adults aged 50 years and older (2 injections)

VAERS DATA & SAE

VAERS Vaccine Adverse Event Reporting System
www.vaers.hhs.gov

Adverse events are possible reactions or problems that occur during or after vaccination. Items **2, 3, 4, 5, 6, 17, 18** and **21** are **ESSENTIAL** and should be completed. Patient identity is kept confidential. Instructions are provided on the last two pages.

INFORMATION ABOUT THE PATIENT WHO RECEIVED THE VACCINE (Use Continuation Page if needed)

1. Patient name: (first) _____ (last) _____
Street address: _____
City: _____ State: _____ County: _____
ZIP code: _____ Phone: () _____ Email: _____

2. Date of birth: (mm/dd/yyyy) _____ 3. Sex: ☐ Male ☐ Female ☐ Unknown

4. Date and time of vaccination: (mm/dd/yyyy) _____ Time: hh:mm _____ AM/PM _____

5. Date and time adverse event started: (mm/dd/yyyy) _____ Time: hh:mm _____ AM/PM _____

6. Age at vaccination: _____ Years _____ Months 7. Today's date: (mm/dd/yyyy) _____

8. Pregnant at time of vaccination?: ☐ Yes ☐ No ☐ Unknown
(If yes, describe the event, any pregnancy complications, and estimated due date if known in item 18)

9. Prescriptions, over-the-counter medications, dietary supplements, or herbal remedies being taken at the time of vaccination: _____

10. Allergies to medications, food, or other products: _____

11. Other illnesses at the time of vaccination and up to one month prior: _____

12. Chronic or long-standing health conditions: _____

INFORMATION ABOUT THE PERSON COMPLETING THIS FORM

13. Form completed by: (name) _____
Relation to patient: ☐ Healthcare professional/staff ☐ Patient (yourself)
☐ Parent/guardian/caregiver ☐ Other: _____
Street address: _____ ☐ Check if same as item 1
City: _____ State: _____ ZIP code: _____
Phone: () _____ Email: _____

14. Best doctor/healthcare professional to contact about the adverse event: Name: _____
Phone: () _____ Ext: _____

INFORMATION ABOUT THE FACILITY WHERE VACCINE WAS GIVEN

15. Facility/clinic name: _____ Fax: () _____
Street address: _____ ☐ Check if same as item 13
City: _____ State: _____ ZIP code: _____
Phone: () _____

16. Type of facility: (Check one)
☐ Doctor's office, urgent care, or hospital
☐ Pharmacy or store
☐ Workplace clinic
☐ Public health clinic
☐ Nursing home or senior living facility
☐ School or student health clinic
☐ Other: _____
☐ Unknown

WHICH VACCINES WERE GIVEN? WHAT HAPPENED TO THE PATIENT?

17. Enter all vaccines given on the date listed in item 4: (Route is HOW vaccine was given, Body site is WHERE vaccine was given)

| Vaccine (type and brand name) | Manufacturer | Lot number | Route | Body site | Dose number in series |
|-------------------------------|--------------|------------|--------|-----------|-----------------------|
| select | select | select | select | select | select |
| select | select | select | select | select | select |
| select | select | select | select | select | select |
| select | select | select | select | select | select |

18. Describe the adverse event(s), treatment, and outcome(s), if any: (symptoms, signs, time course, etc.) _____
Use Continuation Page if needed

19. Medical tests and laboratory results related to the adverse event(s): (include dates) _____
Use Continuation Page if needed

20. Has the patient recovered from the adverse event(s)?: ☐ Yes ☐ No ☐ Unknown

21. Result or outcome of adverse event(s): (Check all that apply)
☐ Doctor or other healthcare professional office/clinic visit
☐ Emergency room/department or urgent care
☐ Hospitalization: Number of days (if known) _____
Hospital name: _____ City: _____ State: _____
☐ Prolongation of existing hospitalization (vaccine received during existing hospitalization)
☐ Life threatening illness (immediate risk of death from the event)
☐ Disability or permanent damage
☐ Patient died – Date of death: (mm/dd/yyyy) _____
☐ Congenital anomaly or birth defect
☐ None of the above

ADDITIONAL INFORMATION

22. Any other vaccines received within one month prior to the date listed in item 4:

| Vaccine (type and brand name) | Manufacturer | Lot number | Route | Body site | Dose number in series | Date Given |
|-------------------------------|--------------|------------|--------|-----------|-----------------------|------------|
| select | select | select | select | select | select | select |
| select | select | select | select | select | select | select |

23. Has the patient ever had an adverse event following any previous vaccine?: (If yes, describe adverse event, patient age at vaccination, vaccination dates, vaccine type, and brand name)
☐ Yes ☐ No ☐ Unknown

24. Patient's race: ☐ American Indian or Alaska Native ☐ Asian ☐ Black or African American ☐ Native Hawaiian or Other Pacific Islander
(Check all that apply) ☐ White ☐ Unknown ☐ Other: _____

25. Patient's ethnicity: ☐ Hispanic or Latino ☐ Not Hispanic or Latino ☐ Unknown

26. Immuniz. proj. report number: (Health Dept. use only) _____

- **Vaccine Adverse Event Reporting System (VAERS)** is a database of adverse event reports submitted by healthcare professionals, patients, caregivers, etc.
- No. reports submitted in 2023: **106,125** (48,438 in 2019)
- Data comprises information about **vaccine** administered, **adverse events** (symptom, outcome, etc.), and **patient** information.
- **Serious Adverse Event (SAE)** is an event with serious patient outcomes including death, ER visit, hospitalization and/or prolonged hospitalization, disability or permanent damage.

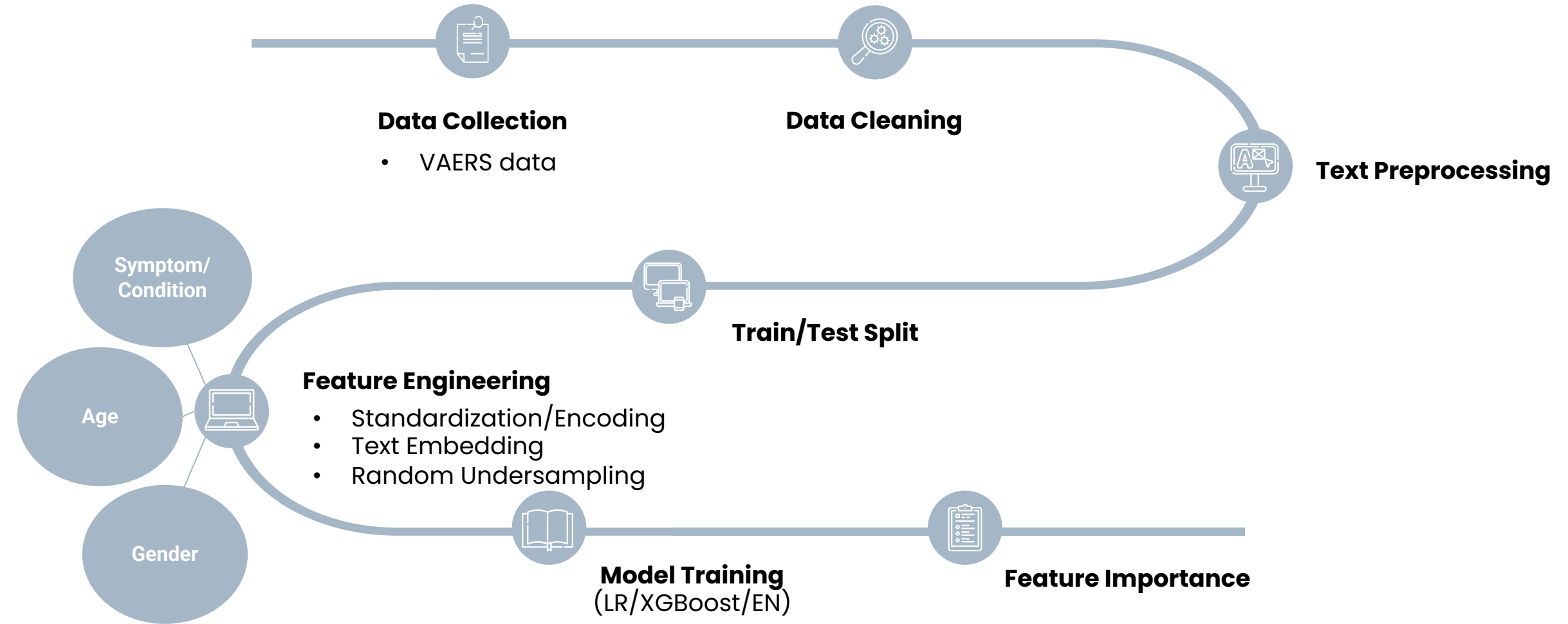
02 PREDICTIVE MODELLING - METHOD

Question:

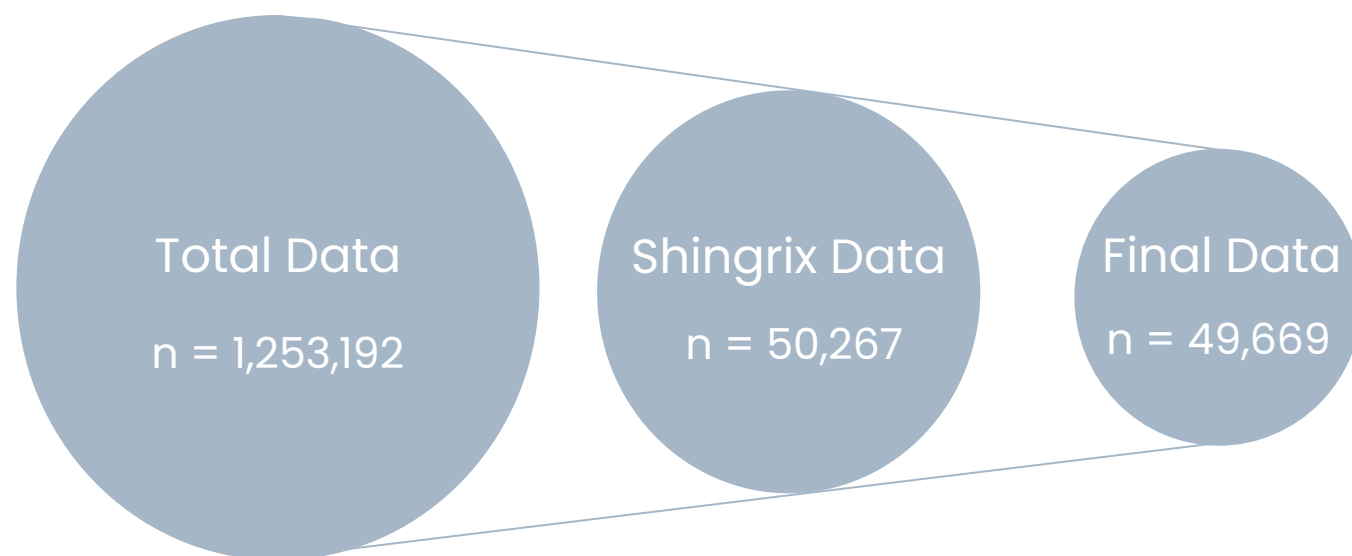
When a patient starts to show signs of adverse events following vaccination, can we predict whether this will progress into serious adverse events?



PROCESS OVERVIEW



DATA EXPLORATION & CLEANING



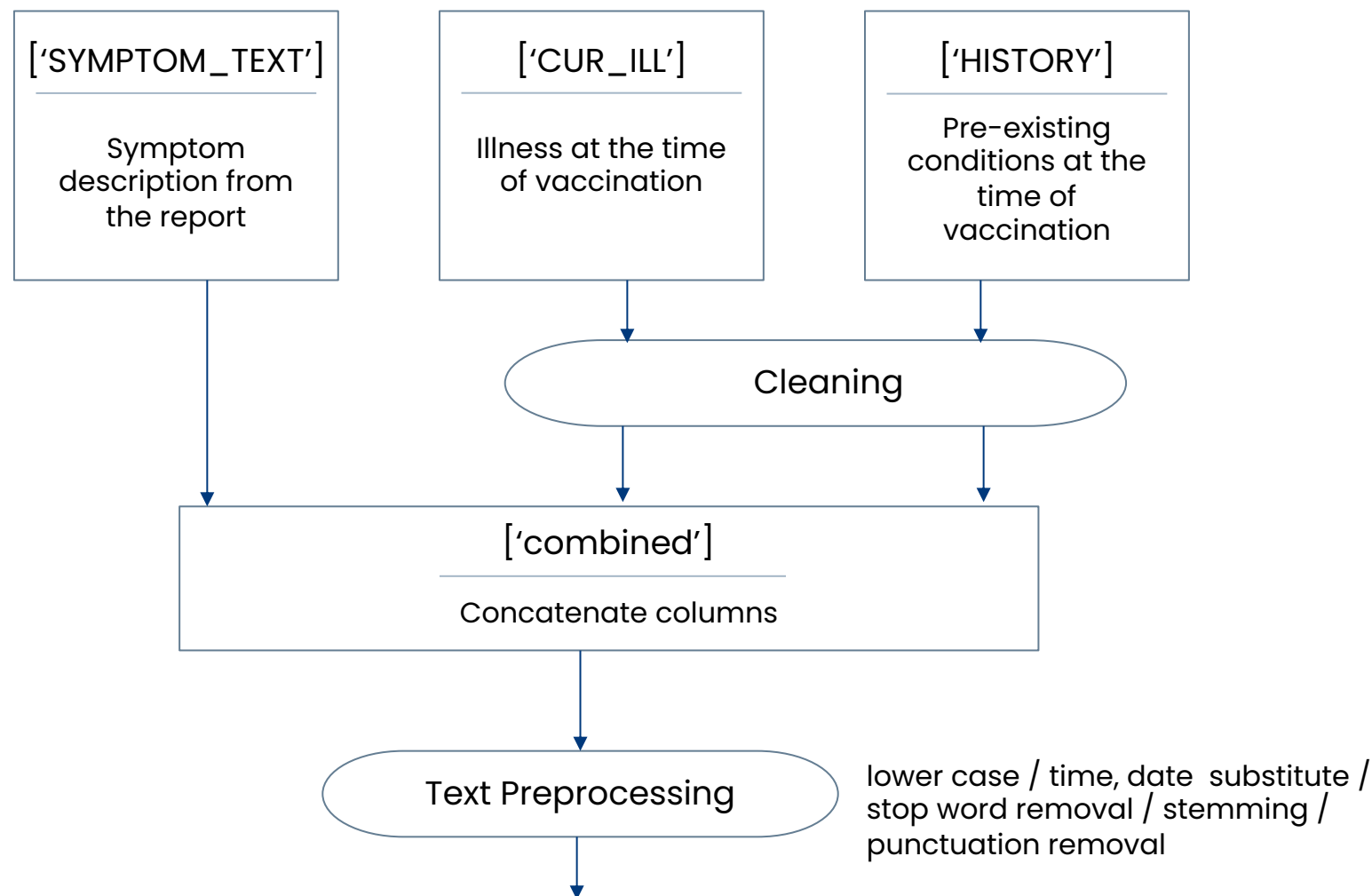
- From year 2018 to 2023
- Significant increase following covid vaccine
- 2018-2020 approx. 49,000 reports/year

- Vaccine : Shingrix
- Age : 50 years +

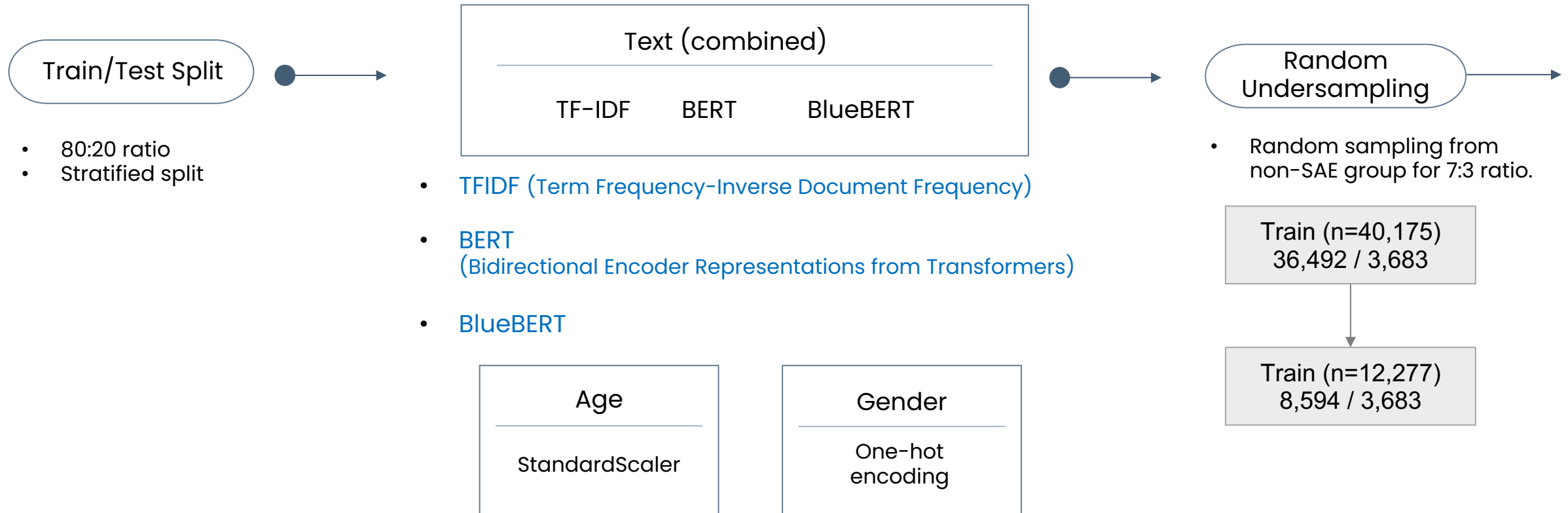
- Symptom NA removed
- Gender 'U' removed
- Symptom 'none stated' removed

- ✓ This study focused on data collected between **2018 and 2023** regarding Shingrix vaccine, which was approved by the FDA in 2017.
- ✓ The data included reports from patients aged **50 and older** who received the vaccine.
- ✓ To ensure data quality, rows with no symptom information and cases with unknown gender were removed from the analysis.
- ✓ From total final data of **49,669 reports**, 45,084 were classified as SAE and 4,585 as non-SAE, representing approximately **10%**.

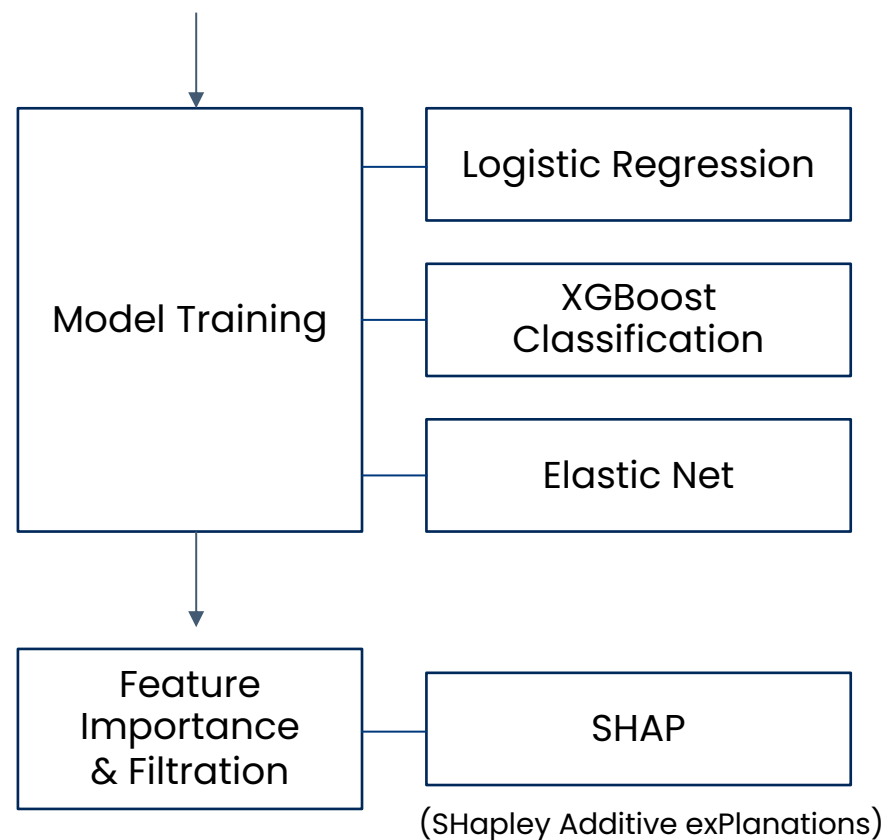
TEXT PREPROCESSING



FEATURE ENGINEERING



MODEL TRAINING & FEATURE IMPORTANCE

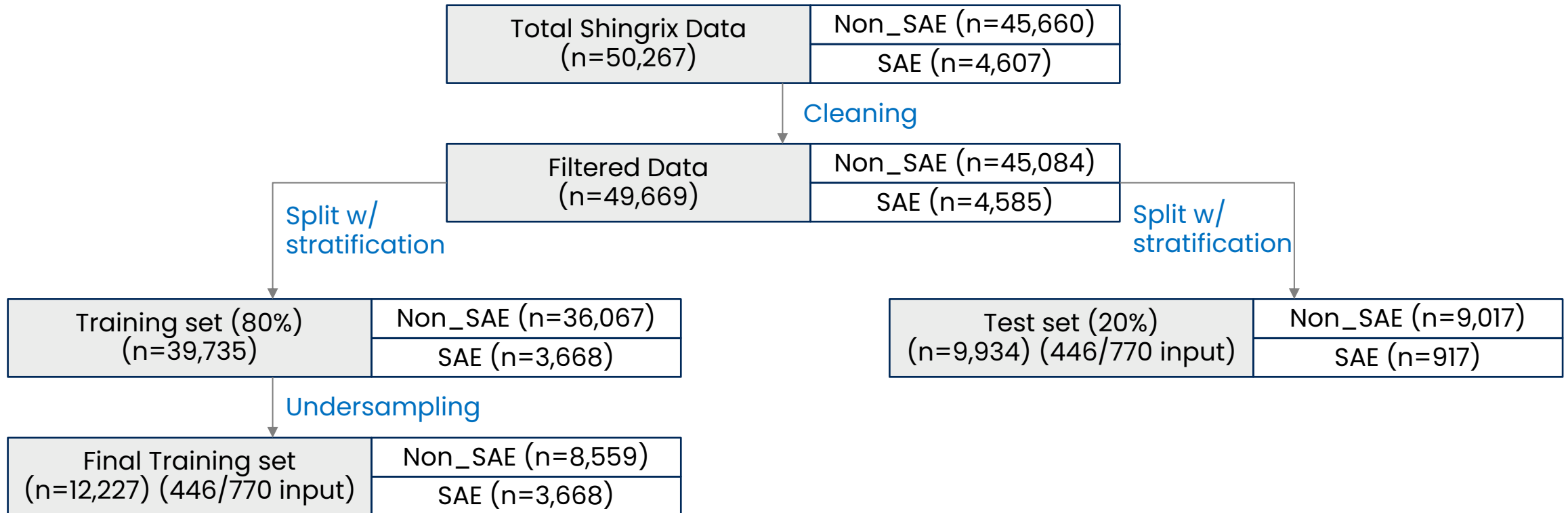


03 PREDICTIVE MODELLING - RESULTS



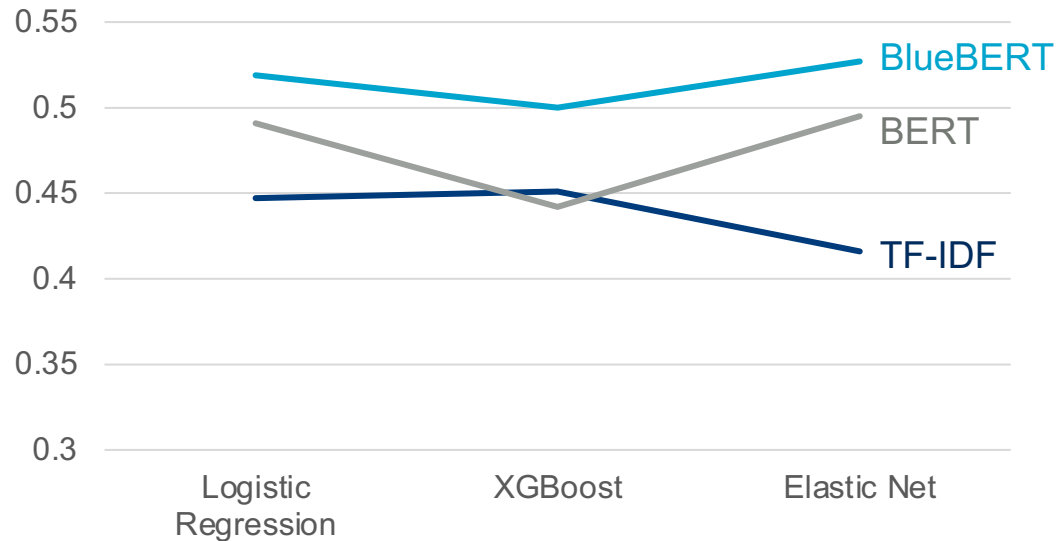
DATA PROCESSING RESULT

Data Preprocessing and Model Training Workflow



MODEL PERFORMANCE

AUPRC Comparison

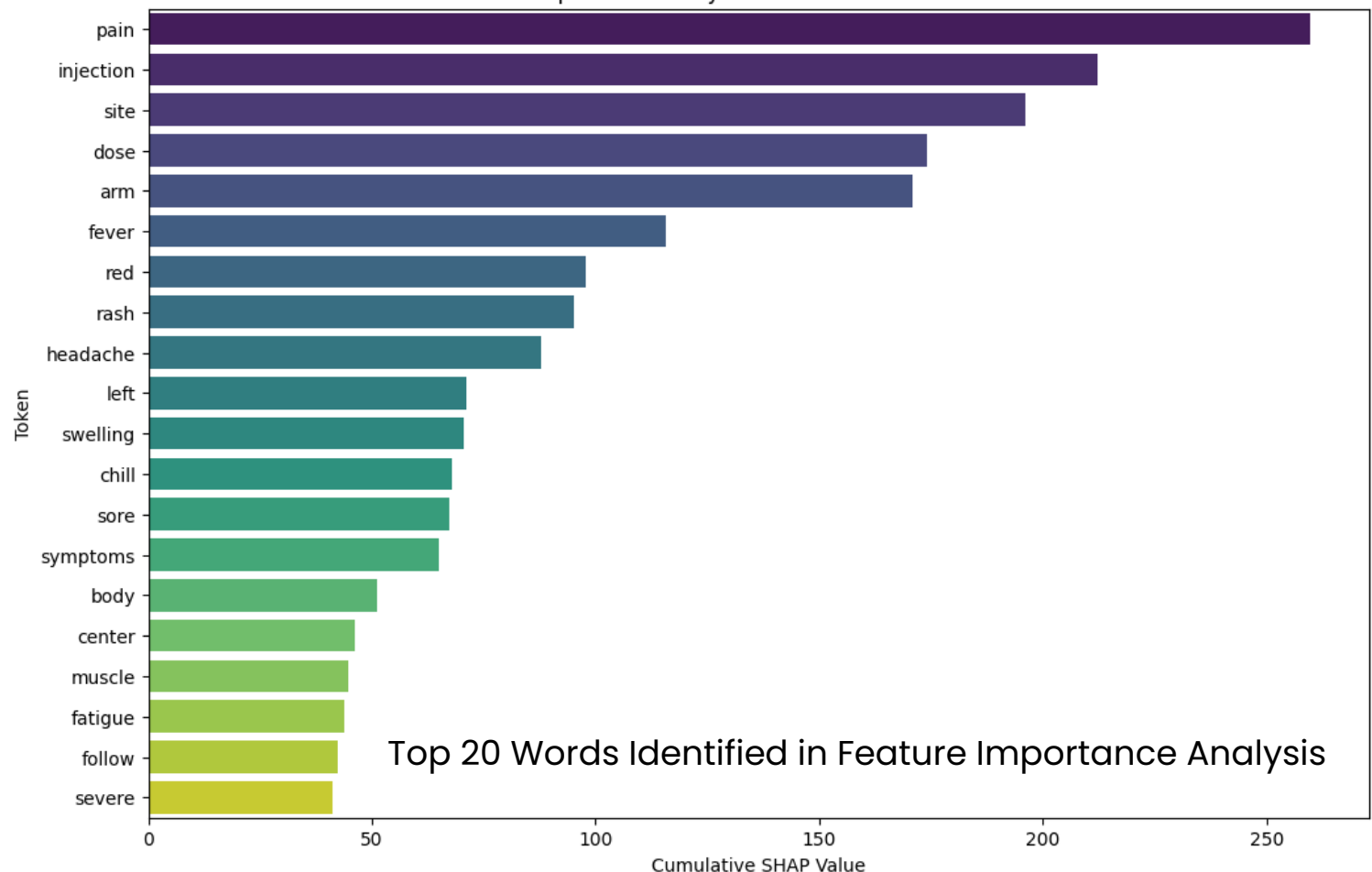


| Feature extraction | TF-IDF | | | | | | BERT-base | | | | | | BlueBERT | | | | | |
|--------------------|--------|-------|---------|-------|-------|-------|-----------|-------|---------|-------|-------|-------|----------|-------|---------|-------|-------|-------|
| | LR | | XGBoost | | EN | | LR | | XGBoost | | EN | | LR | | XGBoost | | EN | |
| Model | Train | Test | Train | Test | Train | Test | Train | Test | Train | Test | Train | Test | Train | Test | Train | Test | Train | Test |
| AUROC | 0.714 | 0.701 | 0.863 | 0.707 | 0.639 | 0.646 | 0.784 | 0.736 | 0.890 | 0.688 | 0.753 | 0.73 | 0.785 | 0.750 | 0.885 | 0.724 | 0.757 | 0.742 |
| Sensitivity | 0.507 | 0.494 | 0.751 | 0.514 | 0.319 | 0.337 | 0.64 | 0.571 | 0.793 | 0.449 | 0.575 | 0.539 | 0.634 | 0.582 | 0.781 | 0.515 | 0.571 | 0.549 |
| Specificity | 0.92 | 0.908 | 0.975 | 0.901 | 0.959 | 0.955 | 0.927 | 0.901 | 0.986 | 0.927 | 0.932 | 0.921 | 0.936 | 0.917 | 0.990 | 0.933 | 0.944 | 0.936 |
| PPV | 0.731 | 0.353 | 0.929 | 0.344 | 0.769 | 0.434 | 0.791 | 0.371 | 0.960 | 0.384 | 0.783 | 0.408 | 0.810 | 0.418 | 0.971 | 0.440 | 0.813 | 0.464 |
| NPV | 0.813 | 0.946 | 0.901 | 0.948 | 0.767 | 0.934 | 0.858 | 0.954 | 0.918 | 0.943 | 0.837 | 0.952 | 0.856 | 0.956 | 0.913 | 0.950 | 0.837 | 0.953 |
| F-1 score | 0.599 | 0.411 | 0.83 | 0.412 | 0.451 | 0.379 | 0.708 | 0.45 | 0.869 | 0.414 | 0.663 | 0.465 | 0.711 | 0.486 | 0.866 | 0.474 | 0.671 | 0.503 |
| AUPRC | 0.693 | 0.447 | 0.877 | 0.451 | 0.646 | 0.416 | 0.77 | 0.491 | 0.908 | 0.442 | 0.743 | 0.495 | 0.777 | 0.519 | 0.909 | 0.500 | 0.756 | 0.527 |
| Accuracy | 0.796 | 0.87 | 0.908 | 0.865 | 0.767 | 0.898 | 0.841 | 0.871 | 0.928 | 0.883 | 0.825 | 0.885 | 0.846 | 0.886 | 0.927 | 0.895 | 0.832 | 0.900 |

- Across various text feature extraction and model combinations, BlueBERT outperformed TF-IDF and BERT-base, demonstrating superior capability in the biomedical domain.
- BlueBERT processed feature with elastic net model ($C=0.1$, $\text{ratio}=0.3$) achieved the highest metrics, indicating enhanced performance in identifying positive cases.
- Compared to baseline (TF-IDF/LR model) the performance improved by 18%.

FEATURE IMPORTANCE

Top 20 Tokens by Cumulative SHAP Value



Adverse Event Data from SHINGRIX Clinical Trial

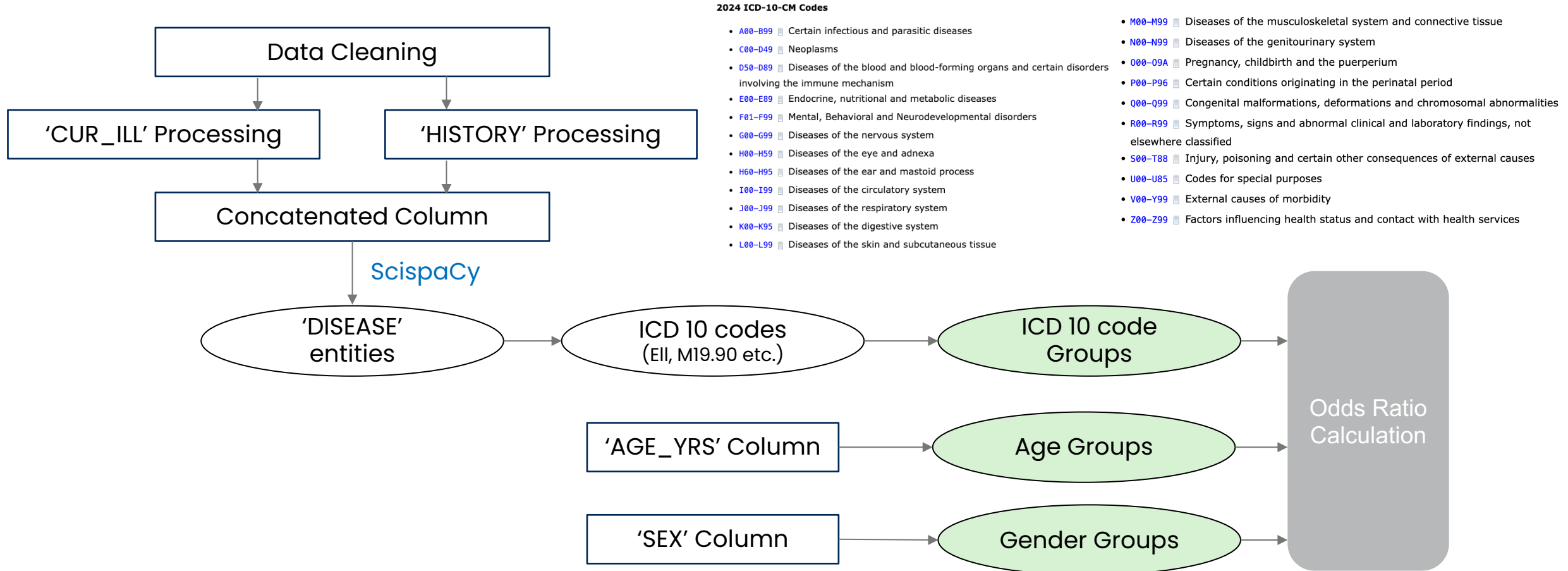
| Adverse Reactions | Aged 50-59 Years | | Aged 60-69 Years | | Aged ≥70 Years | |
|----------------------------------|------------------|----------------------|------------------|----------------------|------------------|----------------------|
| | SHINGRIX | Placebo ^c | SHINGRIX | Placebo ^c | SHINGRIX | Placebo ^c |
| Local Adverse Reactions | n = 1,315 | n = 1,312 | n = 1,311 | n = 1,305 | n = 2,258 | n = 2,263 |
| | % | % | % | % | % | % |
| Pain | 88 | 14 | 83 | 11 | 69 | 9 |
| Pain, Grade 3 ^d | 10 | 1 | 7 | 1 | 4 | 0.2 |
| Redness | 39 | 1 | 38 | 2 | 38 | 1 |
| Redness, >100 mm | 3 | 0 | 3 | 0 | 3 | 0 |
| Swelling | 31 | 1 | 27 | 1 | 23 | 1 |
| Swelling, >100 mm | 1 | 0 | 1 | 0 | 1 | 0 |
| General Adverse Reactions | n = 1,315 | n = 1,312 | n = 1,309 | n = 1,305 | n = 2,252 | n = 2,264 |
| | % | % | % | % | % | % |
| Myalgia | 57 | 15 | 49 | 11 | 35 | 10 |
| Myalgia, Grade 3 ^e | 9 | 1 | 5 | 1 | 3 | 0.4 |
| Fatigue | 57 | 20 | 46 | 17 | 37 | 14 |
| Fatigue, Grade 3 ^e | 9 | 2 | 5 | 1 | 4 | 1 |
| Headache | 51 | 22 | 40 | 16 | 29 | 12 |
| Headache, Grade 3 ^e | 6 | 2 | 4 | 0.2 | 2 | 0.4 |
| Shivering | 36 | 7 | 30 | 6 | 20 | 5 |
| Shivering, Grade 3 ^e | 7 | 0.2 | 5 | 0.3 | 2 | 0.3 |
| Fever | 28 | 3 | 24 | 3 | 14 | 3 |
| Fever, Grade 3 ^f | 0.4 | 0.2 | 1 | 0.2 | 0.1 | 0.1 |
| GI ^g | 24 | 11 | 17 | 9 | 14 | 8 |
| GI, Grade 3 ^e | 2 | 1 | 1 | 1 | 1 | 0.4 |

- Source: Shingrix prescribing information (FDA)
- Based on 2 studies (NCT01165177 & NCT01165229)

04 SUBGROUP ANALYSIS



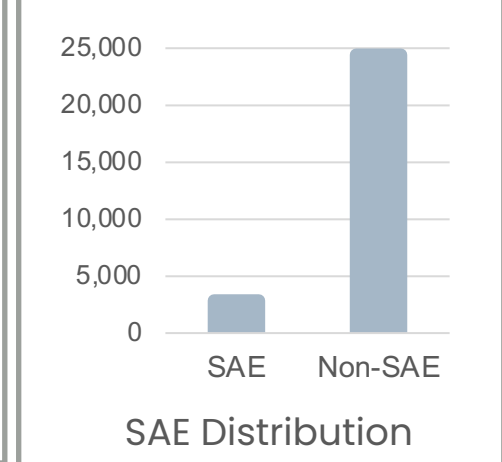
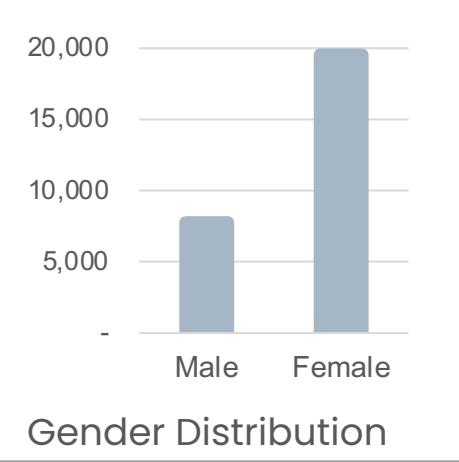
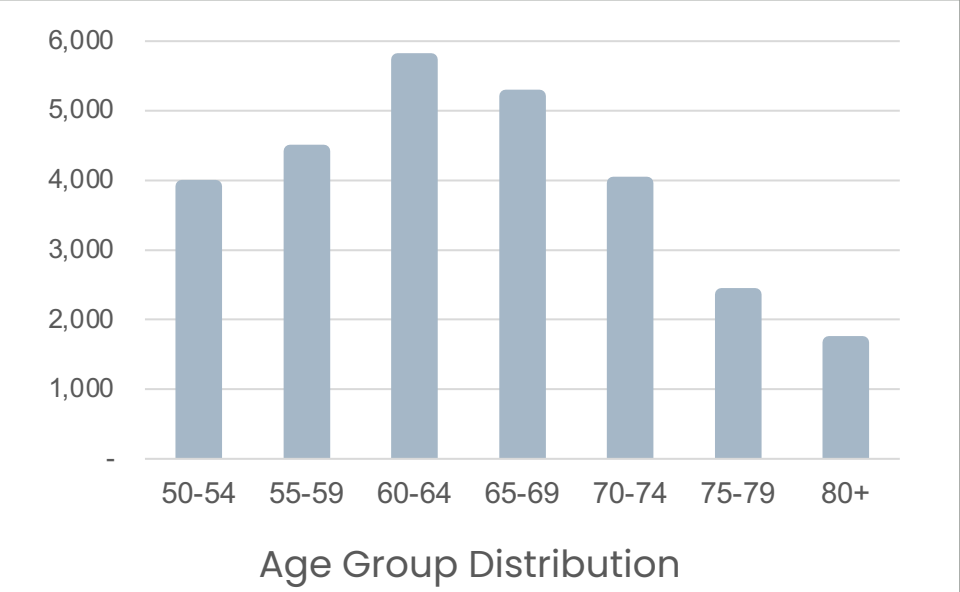
PROCESS OVERVIEW



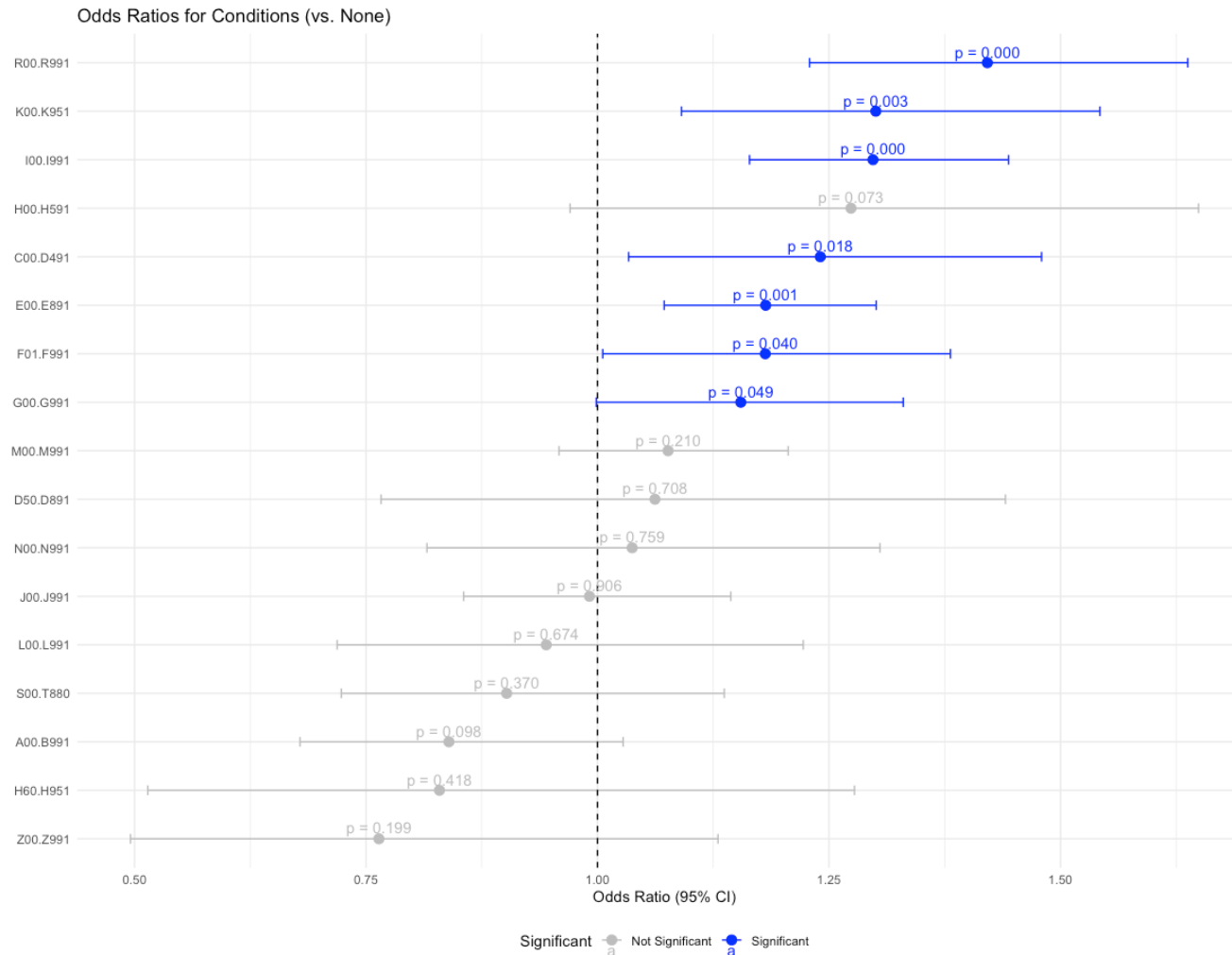
DATA DISTRIBUTION

Conditions Distribution

| Code | Description (Condition Categories) | Count |
|---------|---|-------|
| A00-B99 | Certain infectious and parasitic diseases | 1,343 |
| C00-D49 | Neoplasms | 1,250 |
| D50-D89 | Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism | 400 |
| E00-E89 | Endocrine, nutritional and metabolic diseases | 6,538 |
| F01-F99 | Mental, behavioral and neurodevelopmental disorders | 1,937 |
| G00-G99 | Diseases of the nervous system | 2,288 |
| H00-H59 | Diseases of the eye and adnexa | 599 |
| H60-H95 | Diseases of the ear and mastoid process | 212 |
| I00-I99 | Diseases of the circulatory system | 4,324 |
| J00-J99 | Diseases of the respiratory system | 2,455 |
| K00-K95 | Diseases of the digestive system | 1,417 |
| L00-L99 | Diseases of the skin and subcutaneous tissue | 690 |
| M00-M99 | Diseases of the musculoskeletal system and connective tissue | 4,664 |
| N00-N99 | Diseases of the genitourinary system | 754 |
| O00-O9A | Pregnancy, childbirth and the puerperium | 1 |
| P00-P96 | Certain conditions originating in the perinatal period | 0 |
| Q00-Q99 | Congenital malformations, deformations and chromosomal abnormalities | 77 |
| R00-R99 | Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified | 2,387 |
| S00-T88 | Injury, poisoning and certain other consequences of external causes | 854 |
| U00-U85 | Codes for special purposes | 10 |
| V00-Y99 | External causes of morbidity | 7 |
| Z00-Z99 | Factors influencing health status and contact with health services | 331 |



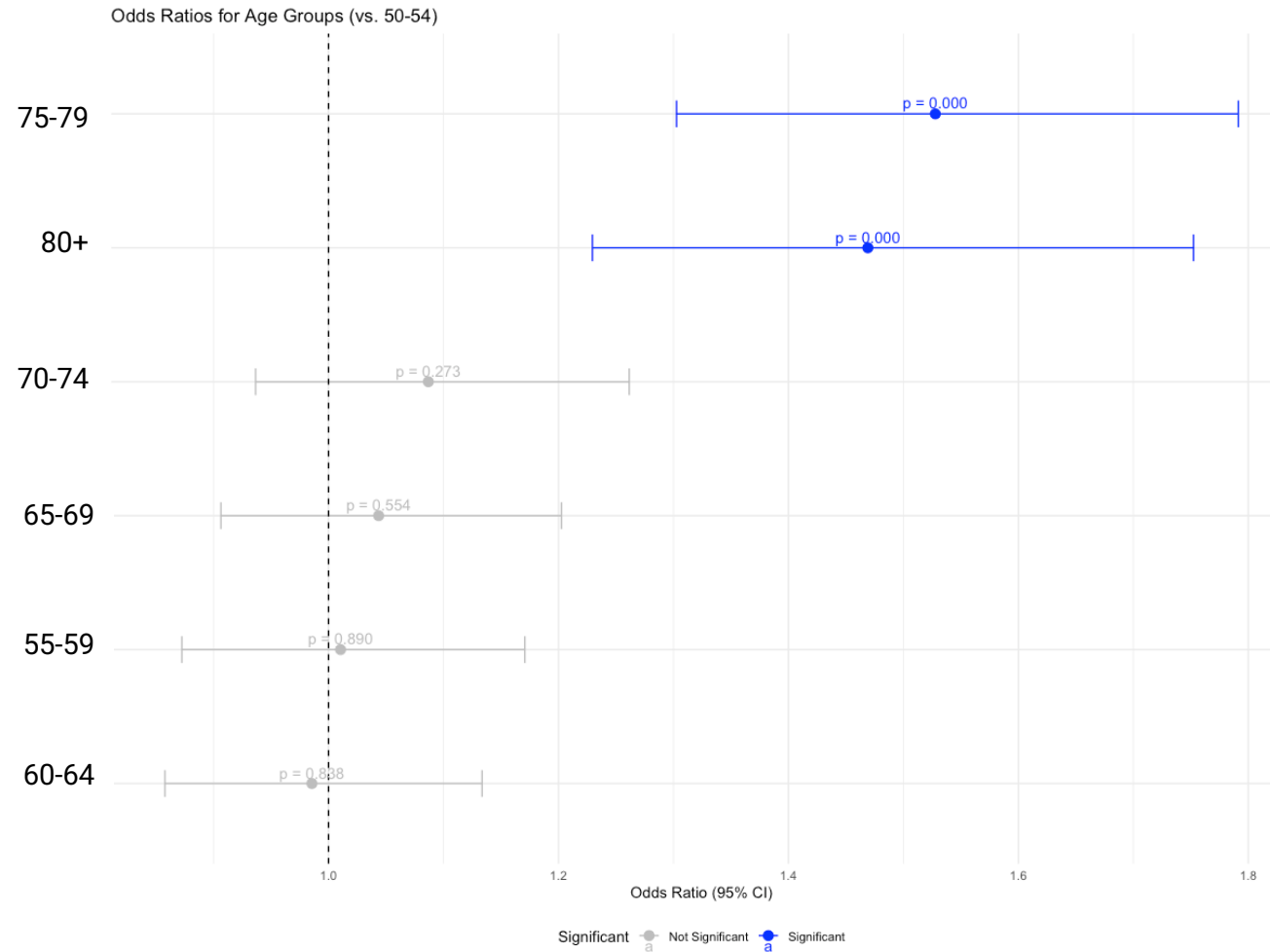
SUBGROUP ANALYSIS RESULTS (VS 'no condition')



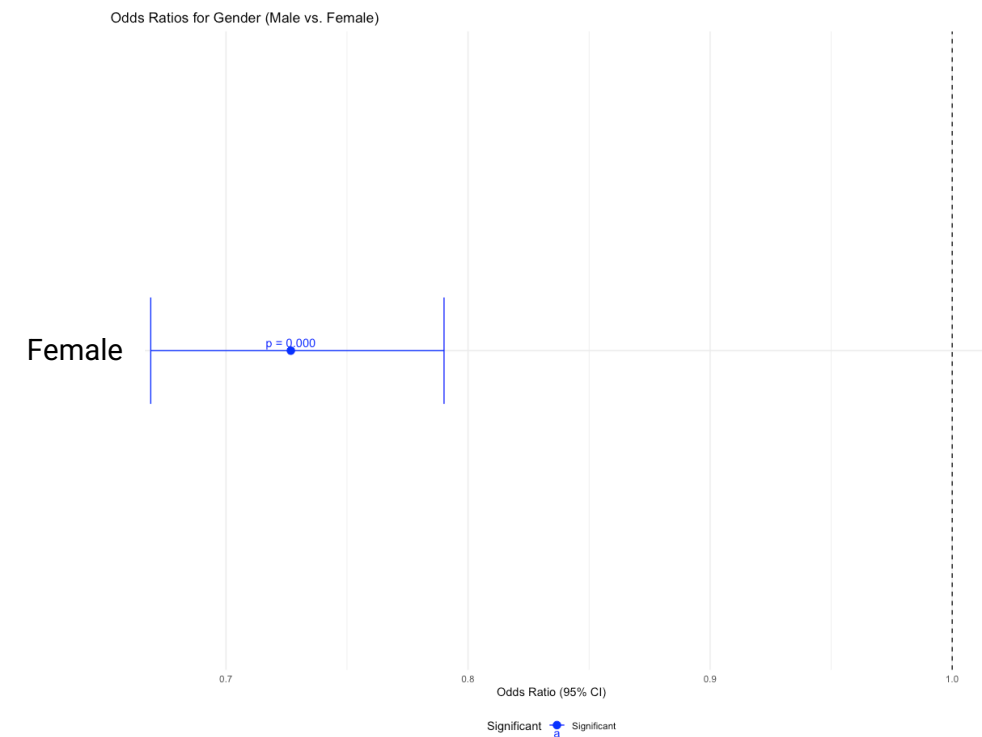
- Individuals with ICD-10 codes R00-R99, K00-K95, I00-I99, C00-D49, E00-E89, F01-F98, and G00-G99 exhibit significantly increased likelihood of SAE compared to those without conditions.
- ICD code groups with lower odds did not show statistically significant results.

| | | |
|---------|---|---------------------|
| R00-R99 | Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified | Cough, rash, fever |
| K00-K95 | Diseases of the digestive system | Acid reflux, ulcer |
| I00-I99 | Diseases of the circulatory system | Hypertension |
| C00-D49 | Neoplasms | Cancer |
| E00-E89 | Endocrine, nutritional and metabolic diseases | Diabetes |
| F01-F98 | Mental, Behavioral and Neurodevelopmental disorders | Depression, anxiety |
| G00-G99 | Diseases of the nervous system | Migraine |

SUBGROUP ANALYSIS RESULTS (VS 50-54, VS male)



- Age groups 70 and older indicated significantly increased odds of SAE occurrence compared to 50-54 age group.
- Female group showed lower odds compared to male group.



05 CONCLUSION & DISCUSSION



DISCUSSION

- BlueBERT + Elastic Net model was superior compared to other models to predict SAE following the onset of AEs using the VAERS dataset with symptom, condition, age, and gender as input features.
- SHAP analysis highlighted the importance of terms such as 'pain', 'fever', 'rash', and 'headache' in predicting SAE, which aligns with clinical trial data.
- Certain ICD code groups (hypertension, diabetes, etc.) and older age groups were linked with higher odds of SAE.

LIMITATIONS

- VAERS data – variable quality in reports, symptom description accuracy, and potential bias from post-SAE reporting.
 - Subgroup analysis (R group with AE symptoms identified as highest odds ratio)
 - Possible SAE information leakage in symptom text

CONCLUSION & FUTURE WORK

- This study enables the prediction of SAE progression at the onset of AEs, allowing for proactive patient care and intervention.
- Statistical analysis identified specific medical conditions, age groups, and gender as risk factors for SAE development, facilitating personalized care decisions.
- Further model refinement (parameters, different models) may improve prediction performance.
- Including additional features (co-administered vaccines, concomitant medications etc.) may provide a more comprehensive understanding.

THANK YOU!

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