

# AI-enabled decision making in drug safety



Oscar Courbit Hermine Tranié  
 Faculty Advisor: Alex Jacquillat  
 Takeda Sponsors: Saurabh Awasthi,  
 Dona M. Ely, Maria Camila Marenco

Pioneering patient safety: Leveraging AI to predict adverse drug outcomes

## Problem Statement

We turned an exploratory project on how to use AI to guide pharmacovigilance into an operational, interactive app that detects adverse events during clinical trials

**\$77-\$138 Billion**  
 annual cost of Adverse Drug Reactions  
 in the US

- How can we **assess our drug's actual impact** compared to other drugs that a patient is taking?
- What are the **key population subgroups** that are at **higher risk of developing a given adverse event**?
- How can we predict **whether a patient is going to develop this adverse event**?

## Data

- Reports from Pharmacovigilance Meetings
- Demographic Information
- Dosage Information
- Historical Conditions

- 3** Drug-Event Combinations
- 100+** Countries
- 37187** Patients
- 250+** Features for each patient
- 0.5%** Proportion of patients with the adverse event studied
- 90k+** Reports of adverse drug reactions

The HEVER group, a global consortium of pharmaceutical R&D heads, shortlisted our project to revolutionize the industry with AI

## Methodology

| CHALLENGE                         | SOLUTION  | IMPACT   |
|-----------------------------------|---|--|
| 1) Multimodal & Unstructured Data | • Natural Language Processing<br>• Graph Concomitant Product Analysis | ➤ Extracted 5000+ Drugs<br>➤ Selected Representative Drugs           |
| 2) Many Concomitant Factors       | • Regress and Compare for Causal Effect of Drugs                      | ➤ Identified 45+ Causal Drugs  |
| 3) High Class Imbalance           | • Ensemble Learning and Undersampling                                 | ➤ Increased AUC from 0.50 to 0.95                                    |
| 4) Need for Interpretability      | • Interpretable Trees<br>• Robustness of Feature Significance         | ➤ Found 5 Highly Significant Features<br>➤ At No Cost on Performance |

## Key Results

**Model 4 AUC Outperforms across DEC**

| DEC    | Model 2 | Model 3 | Model 4 |
|--------|---------|---------|---------|
| DEC #1 | 0.63    | 0.67    | 0.88    |
| DEC #2 | 0.5     | 0.68    | 0.95    |
| DEC #3 | 0.76    | 0.81    | 0.82    |

**Causal drugs findings**

- taking **enoxaparin** (blood thinner) increases on average by **28%** the risk of cardiac disorder (between 6 and 50%)
- taking **ondansetron hydrochloride** (anti-vomiting) increases on average by **12%** the risk of cardiac disorder (between 0 and 25%)

**Tree to interpret model decisions**

eg. Patients who submitted **more than 6 previous events** and had an **average dose > 126.6mg** are **more likely to face a cardiac disorder**

**You can find all the results in our fully automated WebApp!**

## Performance

| DEC #1 | Model 2 | Model 3 | Model 4 | DEC #1 | Model 2 | Model 3 | Model 4 | DEC #1 | Model 2 | Model 3 | Model 4 | Ensemble Model AUC | Tree Model AUC | Tree Model Representativeness |     |
|--------|---------|---------|---------|--------|---------|---------|---------|--------|---------|---------|---------|--------------------|----------------|-------------------------------|-----|
| TPR    | 0.75    | 0.65    | 1.00    | TPR    | 0.75    | 0.65    | 1.00    | TPR    | 0.75    | 0.65    | 1.00    | DEC #1             | 0.88           | 0.91                          | 87% |
| FPR    | 0.04    | 0.16    | 0.28    | FPR    | 0.04    | 0.16    | 0.28    | FPR    | 0.04    | 0.16    | 0.28    | DEC #2             | 0.95           | 0.86                          | 94% |
|        |         |         |         |        |         |         |         |        |         |         |         | DEC #3             | 0.82           | 0.81                          | 98% |

## Decision Making Framework

**R&D** | **Clinical Trial** | **Marketing**

decision-making flexibility: high, mid, low

AUC: 50%, 70%, 95%

- Do we continue developing this drug?**  
Predict adverse event based on demographics data
- Is there a causal relationship between the initiation of the Takeda product and the adverse event?**  
Analyze influence from other drugs
- Do we market this drug?**  
Add dosage information to prediction
- What do we add to the label?**  
Add initial light reaction

time: Day 0, Day 3, Day 11, Day 37

data: Jane Doe, 43-year-old woman from Japan with type 1 diabetes and daily painkiller intake, gets a prescription for the Takeda drug; Jane Doe starts the Takeda drug: twice a day in a capsule; Jane Doe first reports intense diarrhea to her doctor; Adverse reaction: Cardiac Arrest

## Impact

Fully automated WebApp to support efficient decision-making

| PRECISION EMPowerMENT   | UNVEILING DANGER   |
|---|--|
| 1) Empowering Patient Confidence<br>Refined drug labels empower patients                | 5) Informed Risk Reduction<br>Expert insight into dangerous drug combinations                |
| 2) Vigilance in Vulnerability<br>Swift identification of susceptible patient subgroups  | 6) Hidden Beneath the Surface<br>Unveiling and preventing potential adverse events           |
| TAILORED CARE   | BRIDGING BOUNDARIES  |
| 3) Preserving Patient Well-being<br>Thousands of patients spared from adverse reactions | 7) Revolutionizing Generalizations<br>Bridging clinical trials to real-world patient benefit |
| 4) Global Influence, Individual Lives<br>Impact on millions through Takeda's reach      | 8) Empowerment Through Adaptation<br>Dynamic research redirection for ongoing patient safety |

- **Massive Patient Impact:** 31 million patients across 100+ countries trust Drug 2 yearly; our safety efforts enhance their lives.
- **Preventing Hidden Risks:** ~30,000 adverse reactions known, countless more prevented by Takeda's vigilance, shielding patients from harm