

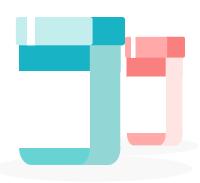
### Providing data driven estimations for

Providing data driven estimations for clinical trial durations



#### Adeline Chin, Cynthia Xu, Jooyeon Hahm

2024 Summer 210 Capstone Section 6



### **Our Team**



**ADELINE CHIN** 

Subject matter expert Frontend Developer

**CLINICAL** 



**CYNTHIA XU** 

Data & ML Engineering Lead Backend Developer



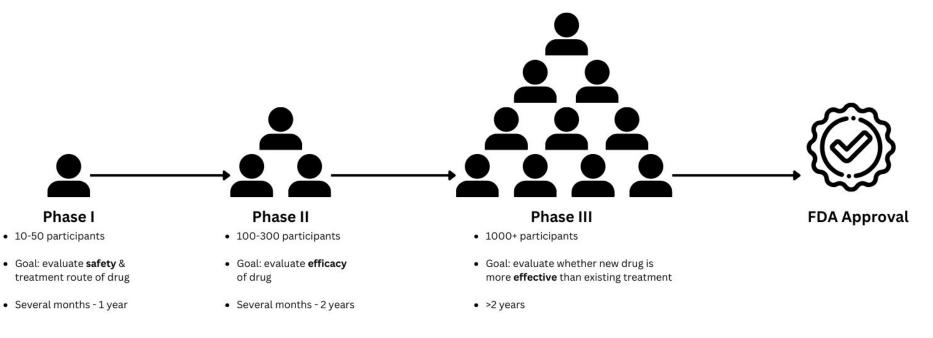
#### **JOOYEON HAHM**

ML Research & DL Lead Website Developer

## Motivation



# Clinical Trials are essential for the innovation and delivery of new drugs



# Phase 3 clinical trials have a high risk of failure due to complexity and duration

#### BIOTECH

### UPDATE: Acelyrin points to CRO error that could explain shocking phase 3 failure

By Annalee Armstrong • Nov 28, 2023 5:00am INDUSTRY NEWS

<sup>1</sup>Armstrong, A. (2023, November 28). Update: Acelyrin points to Cro error that could explain shocking phase 3 failure. Fierce Biotech.

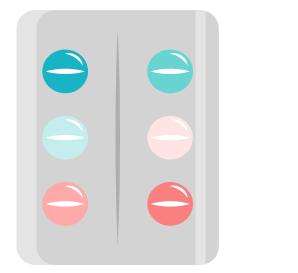
<sup>2</sup>Schmidt, H. (2023, August 11). Nektar sues Eli Lilly for incorrect clinical trial results. PharmaNewsIntelligence.

### CLINICAL

### Nektar Sues Eli Lilly for Incorrect Clinical Trial Results

The immunology firm is suing its big pharma partner after clinical trial data failed to fully demonstrate the positive impact of an atopic dermatitis drug. Aug 11, 2023

# Despite a large market size, a publicly accessible tool for predicting trial durations is lacking.



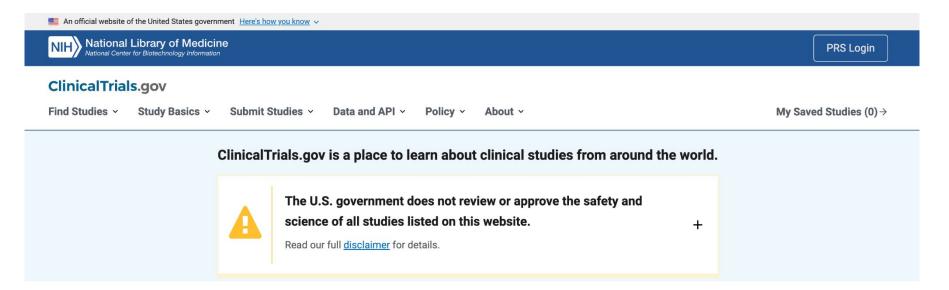
## Estimated \$55.86 billion global market value for CROs

## **39,722** new clinical trials registered in 2023 at clinicaltrials.gov

1. Pawar, N. (2024). Clinical Trials Market Size, Growth and Statistics 2030. Vision Research Reports. https://www.visionresearchreports.com/report/checkout/38176

 National Library of Medicine: National Center for Biotechnology Information. (2024). Trends and Charts on Registered Studies. National Library of Medicine: National Center for Biotechnology Information <u>https://clinicaltrials.gov/about-site/trends-charts</u>

### ClinicalTrials.gov is a global registry for clinical trials. We leveraged 19K post-2011 oncology studies to build our models.



# Existing trial management solutions fail to specifically predict trial durations.





## Our goal

Develop a ML tool for CROs that predicts the duration intervals of Phase 3 clinical trials from study protocol data



## **Minimum Viable Product**



### **MVP Demo**

| 0.0000000000000000000000000000000000000 |  |  |
|---|--|--|
| A                                       |  |  |
|   |  |  |
|   | B (mean)   |  |
|   | () improve   |  |
|   | C Brandon -  |  |
|   | Th Insertion   |  |
|   | (d). Searching prior of period (searching)   |  |
|   | 1  |  |
|   | <ul> <li>Weisse Accounting (Sample Party)</li> </ul>   |  |
|   | (Terrat August +   |  |
|   | j manufal  |  |
|   | These land   |  |
|   | And Article and Ar       |  |
|   |  |  |
|   | Nation   |  |
|   | <ol> <li>Steps Service (set) (set) (set)</li> </ol>  |  |
|   |  |  |
|   |  |  |
|   | <ol> <li>Alars in the second seco</li></ol> |  |
|   | Tagenter Market  |  |
|   |  |  |
|   |  |  |

## Modeling & Feature Engineering



# RandomForest Classification gave the best predictive performance

<u>ClinicalTrials.gov Dataset</u>: completed Phase 3 oncology trials, n=1,634

| Model              | Purpose    | Number<br>of Bins | Accuracy | Mean<br>Accuracy<br>K-fold | Precision | MAE   |
|--------------------|------------|-------------------|----------|----------------------------|-----------|-------|
| RF                 | baseline   | 3                 | 0.245    | 0.420                      | 0.235     | 1.137 |
| RF + text features | prediction | 3                 | 0.602    | 0.603                      | 0.592     | 0.447 |

# We extracted novel features from human-written study protocol fields

| Example raw text from study protocol  | Output   | Feature  |
|---|--|--|
| {'measure': 'Difference in mean left anterior descending coronary artery (LAD) mean<br>normal tissue dose (NTDmean) (group B)',, 'timeFrame': 'End of radiotherapy (3-4<br>weeks)'}   | 3-4 weeks =<br>28 days                         | Time to measure primary<br>AND/OR secondary<br>outcomes            |
| <ul> <li>Inclusion Criteria:</li> <li>Complete microscopic excision of early stage invasive ductal or lobular carcinoma (pT1-3b N0-1 M0) of the left breast following breast conservation surgery or mastectomy.</li> <li>Recommendation for whole breast (groups A and B) or chest wall (Group A only) radiotherapy (with or without tumour bed boost)</li> <li>Age ≥18</li> <li>Exclusion Criteria:</li> <li>Requirement for nodal irradiation</li> <li>Patients with micro- or macro-scopic disease on sentinel node biopsy who have not undergone completion axillary node clearance</li> </ul> | 3 criteria<br>2 criteria                       | Number of inclusion<br>criteria<br>Number of exclusion<br>criteria |
| {'measure': 'Overall patient survival rate', 'description': 'The median overall patient<br>survival rate assessed by Kaplan-Meier analysis and log-rank test for treatment<br>comparisons.', 'timeFrame': 'up to 4 years after randomization'}  | <b>True =</b><br>measuring<br>overall survival | Overall survival outcome   |

### Our novel features were ranked as most important

| Feature                              | Importance | Extracted from Protocol Text? |
|--------------------------------------|------------|-------------------------------|
| Time to measure secondary outcomes   | 0.152      |                               |
| Time to measure primary outcomes     | 0.138      |                               |
| Number of patients enrolled          | 0.099      |                               |
| Number of patient inclusion criteria | 0.081      |                               |
| Number of patient exclusion criteria | 0.072      |                               |
| Number of study locations            | 0.071      |                               |
| Measuring overall survival outcome   | 0.043      |                               |

## **Technical Takeaways**



### Key learnings

• Study protocol data alone is not sufficient for high accuracy predictions of trial duration

• Using LLMs for feature extraction is difficult with jargon-heavy text

• Our model trained on Phase I data shows promise for outperforming the current best published duration prediction model

### **Future Work**

#### **NLP Feature Extraction**

Further explore NLP techniques for feature extraction

#### **User Testing**

Get feedback from CRO users

#### Publication

Publish novel Phase I model findings

### **Our mission**

Improve the quality and efficiency of clinical trials to better deliver novel therapeutic solutions to patients in need



### Acknowledgements

Thank you to Puya & Korin for technical guidance.

Thank you to Stephanie Wong for UX design and branding.

Thank you to our fellow Capstone classmates.

Thank you to our pets for stress relief and emotional support.

Template by Slidesgo.



### References

- 1. Armstrong, A. (2023, November 28). Update: Acelyrin points to Cro error that could explain shocking phase 3 failure. Fierce Biotech. https://www.fiercebiotech.com/biotech/acelyrin-blames-cro-error-shocking-phase-3-failure-sent-shiver-through-biotech-ipo-market
- 2. Schmidt, H. (2023, August 11). Nektar sues Eli Lilly for incorrect clinical trial results. PharmaNewsIntelligence. https://pharmanewsintel.com/news/nektar-sues-eli-lilly-for-incorrect-clinical-trial-results
- 3. Long, B., Lai, S. W., Wu, J., & Bellur, S. (2023). Predicting Phase 1 Lymphoma Clinical Trial Durations Using Machine Learning: An In-Depth Analysis and Broad Application Insights. Clinics and Practice, 14(1), 69-88.
- 4. Hutchison, E., Zhang, Y., Nampally, S., Neelufer, I. K., Malkov, V., Weatherall, J., ... & Shameer, K. (2021). Modeling Clinical Trial Attrition Using Machine Intelligence: A driver analytics case study using 1,325 trials representing one million patients. medRxiv, 2021-11.
- 5. Kavalci, E., & Hartshorn, A. (2023). Improving clinical trial design using interpretable machine learning based prediction of early trial termination. Scientific reports, 13(1), 121.
- 6. Wu, K., Wu, E., DAndrea, M., Chitale, N., Lim, M., Dabrowski, M., ... & Zou, J. (2022). Machine learning prediction of clinical trial operational efficiency. The AAPS Journal, 24(3), 57.
- 7. Markey, N., Howitt, B., El-Mansouri, I., Schwartzenberg, C., Kotova, O., & Meier, C. (2024). Clinical trials are becoming more complex: a machine learning analysis of data from over 16,000 trials. Scientific Reports, 14(1), 3514.