### Challenges and Opportunities with Decentralized Trials: Statistical Perspectives

Demissie Alemayehu, Pfizer Inc.

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# Outline

- Background
- Lessons from the REMOTE Trial
- Elements of DCTs with Statistical Import
- Modern Analytics to Advance DCTs
- Other Considerations in DCTs
- Concluding Remarks

# **Decentralized trials: Terminology**



- Variety of terms in use
- Hybrid approach preferable in certain situations

# **Traditional vs. Decentralized** Clinical Trials

	Traditional	Virtual
Recruitment, Enrollment	• Site visits by patients	<ul><li>Internet &amp; Social Media</li><li>People's online searches and activities</li></ul>
Compliance & Retention	<ul> <li>Site visits by study monitors</li> </ul>	<ul> <li>Remote data verification &amp; patient monitoring</li> </ul>
Safety/efficacy data capture & processing	<ul> <li>Measurements by trained personnel</li> <li>SDV</li> </ul>	<ul><li>ePRO</li><li>Mobile devices</li></ul>
Design and data analysis	<ul> <li>Operational challenges for CID</li> <li>Data sparsity limits ML implementation</li> </ul>	<ul> <li>CID implementation</li> <li>Massive data for training ML methods</li> </ul>

# Why Decentralized Trials in Drug Development?



# **Cost of Pharmaceutical Clinical Trials**



**Source:** Sertkaya A, Wong HH, Jessup A, Beleche T. Key cost drivers of pharmaceutical clinical trials in the United States. *Clin Trials.* 2016;13(2):117-126.doi:10.1177/1740774515625964

## **Cost Drivers of Pharmaceutical Clinical Trials**



Source: https://pubmed.ncbi.nlm.nih.gov/26908540/

# Average Duration (MM) of Oncology Clinical Trials

"... oncology clinical trial delays are a direct result of patient recruitment challenges."



Source: <u>http://ipimediaworld.com/wp-content/uploads/2013/06/2-Patient-Recruitment-Driving-Lenght-and-Cost-of-Oncology-Clinical-Trials.pdf</u>

# **Challenges with Patient Recruitment: Diversity**

#### FDA Analysis of Racial Demographics in Multiple Myeloma Trials

- Blacks constitute 20% MM, but 13% U.S. population
- Median% blacks enrolled in MM trials 4.5%.



# **Conclusion:** Enrollment of black subjects in pivotal trials submitted to FDA not representative of MM population

Source: Bhatnagar, et al. FDA Analysis of Racial Demographics in Multiple Myeloma Trials, Blood, 2017

### **Benefits of Decentralized Trials**





# **Industry Trends**



#### > 75% pharma respondents favor adoption DCTs following pandemic

Source: Oracle. Survey: COVID-19 the Tipping Point for Decentralized Clinical Trials, November 18, 2020



> 84 % pharma sponsors and CROs seek technology use to support DCTs.

Rethinking Data Quality Best Practices in the Era of Decentralized Clinical Trials (premier-research.com)

# An Early Example of DCTs: REMOTE

Research on Electronic Monitoring of Overactive Bladder Treatment Experience (REMOTE) trial (Orri et al. 2014).

- Initiated by Pfizer in 2011
- Designed to replicate previous clinic-based trials of tolterodine ER (Detrole)
- First web-based study conducted under an IND application

#### Features

- Participants recruited and informed consent obtained electronically
- Labs in facilities near their homes
- Drugs shipped directly to participants
- Interactive voice response system (IVRS) used for randomization,
- EDC utilized for data collection and management

#### **Lessons learned**

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- Need to simplify screening criteria.
- User-friendly and state-of-the-art technology

#### Challenges

- Complicated screening process: Security measures to verify participant identification online
- Slow enrollment rates
- Drop-out rate much higher than conventional trials

Main Result: Efficacy observed consistent with results from conventional trials

# Key Drivers of DCTs: Technology & Analytics



### Modern Analytics in Advancing DCTs

#### Advanced Methods FFNN AI Traditional ML RNN CNN ANN:Artificial Deep Auto **Machine** Neural Network **Encoders** Learning (ML) SVM:Support • **Vector Machines** PCA Adversarial k-NN Training Regularized • GANs: **Deep Learning** regression, Generative (DL) adversarial networks

#### Recent developments:

• Inference involving ML models

### Statistical/Digital Opportunities with DCTs



# **Potential Barriers to Recruitment**



# **Digital Solutions to Recruitment Barriers**



# **Digital Solutions: Lessons from Other Industries**

- Business: Al in marketing (Ma et al. 2020)
  - Customer segmentation and engagement
  - > Application in Banking, retail, hospitality, etc.
- Human resources: AI to enhance DEI
  - Recommender systems to raise awareness of job opportunities: Implications for recruitment
  - Mitigation of unconscious bias in performance evaluation: Implication for investigator bias (Zhang et al. 2019).
- **Cautionary measures**: Al perpetuation of harmful biases (Daugherty et al. 2018)

# **Recommender System for Patient Recruitment**

- Approach widely used in other industries
- Recommender system to match patients to clinical trials
- Approach requires:
  - Collecting patient data
  - Identifying patients more likely to sign up for trials
  - Reaching those patients using more targeted advertising
- Potential to improve enrollment
  - Identifies eligible patients, better than traditional approach
  - Saves time and effort
  - Helps planning, with better knowledge of target population
  - Enhances diversity in trials

# **Recommender System (cont.)**



Hybrid approach:

- Helps address 'cold start' problem
  - When new user introduced but cannot be matched due to lack of information on that user.

## **Data Capture and Processing: Traditional Approach**



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# **Digital Solutions: Data Capture and Processing**

Study participants Training **Data review** Ô Data Managers EDC 0 Mobile technology/ IVRT, ePROs Review 5 Trained machine < predicts discrepancies Prediction Prediction Correct in-correct AI and ML for ML to predict and Al -enabled outcome correct data **RBQM** assessment discrepancies

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# **Digital Solutions: Outcome Assessment**

Examples from the literature:

- CNN: Predict depression severity from speech patterns (He et al. 2018)
- SVM: Classify/predict Alzheimer's disease (Collij et al. 2017)
- CNN: Physiological signals anomaly detection (Wang et al 2016)
- Deep Belief Network: Human activity recognition (Yalcin 2016)
- Restricted Boltzmann Machine (RBM): ECG classification (Yan et al 2015)

### FDA framework for Software as a Medical Device (SaMD)

https://www.fda.gov/files/medical%20devices/published/US-FDA-Artificial-Intelligence-and-Machine-Learning-Discussion-Paper.pdf

### **Digital Solutions: Risk-Based Quality Management**

- RBQM:
  - o Ensures early risk detection and prevention
  - o Permits continual risk monitoring
  - Can help identify issues that might not otherwise have been detected
- Commonly used techniques:
  - o Predictive analytics: ML models and data visualization tools
    - Identify key risk indicators
  - o Anomaly detection: branch of ML to identify cases for scrutiny

➢ Regularized logistic reg, SVM, kNNS, etc.

# **Digital Solutions: Foster Innovative Designs**

- Adaptive designs:
  - Provide flexibility to adjust parameters of a trial midstream
    - Shifting patients and resources to promising treatment arms
    - Sample size re-estimation
    - Early stopping for futility or efficacy
- Major obstacles:
  - Statistical challenges
  - Operational challenges

### **Digital Solutions: Foster Innovative Designs (cont.)**



Decision analysis-based designAction wrt expected utility

# Risk Sensitive MABP (Lin, Pang and Alemayehu 2020)

A flexible approach:

- Based on a Bayesian ranking algorithm to maximize expected total rewards
- Permits:
  - Exploration: Correct ranking of treatments
  - Exploitation: Most patients to most effective drug

"Despite ... near-perfect fit between a real-world problem and a mathematical theory, MABP has yet to be applied to an actual clinical trial" (Villar et al. 2015).

• The operational convenience offered by VTs can foster implementation of innovative designs such as MABP

# Measurement Validity in Virtual Trials

Establishment of validity and reliability

- Assess ability to quantify clinical and pathological condition of interest
- Comparability to measurements obtained by established techniques
- Accuracy and precision (i.e., intra- and inter-device variability)

#### Approaches

- Traditional psychometric techniques to assess validity and reliability (see, e.g., Cappelleri et al 2014)
   Easter applying structural equation modeling (SEM), etc.
  - Factor analysis, structural equation modeling (SEM), etc.
- Modern ML tools to establish sensitivity & specificity for high dim data

# Measurement Validity (cont.)

**Reliability**: Extent to which an instrument provides consistent results

• Intraclass correlation coefficient (ICC): Proportion of total variability ( $\sigma_T^2$ ) in observed scores attributable to measurement error ( $\sigma_e^2$ ):

$$\rho = \frac{\sigma_T^2 - \sigma_e^2}{\sigma_T^2}$$

• Wearable device data: Spearman-Brown prophecy formula:

$$\rho_m = \frac{m\rho}{1 + (m-1)\rho}$$

where  $\rho$ , reliability of a single daily measurement; *m*, number of daily measurements averaged

- ICC for agreement between remote vs. traditional trials
   o Lower bound of 95% C.I. > 0.7 indicate comparability (Byrom et al. 2019).
- Cohen's kappa coefficient (κ), agreement for categorical outcomes (McHugh 2021).
  - *κ* ≤ 0 indicate no agreement, 0.61–0.80 and 0.81–1.00, are taken as substantial and almost perfect agreement, respectively.

### **Other Statistical Challenges and Opportunities in DCTs**

Generally, statistical issues similar in DCTs and traditional RCTs



# Other Statistical Challenges & Opportunities (cont.)

Sample Size Determination

- Estimates of variability
  - Impact of technology use on variability of outcome measures
  - o Inter-rater variability vs. variability induced by technology
- Effect Size
  - Effect sizes based on traditional vs. digitally-generated outcome measures
  - Use of historical data to inform effect size determination

### Homogeneity/Poolability of Data

- Consideration for heterogeneity in data collection
- Use of model-based methods: Bayesian hierarchical model with robust pooling, incorporating change in practice over time
- Power and *post hoc* analyses implications (Eremenco et al. 2014).

# Other Statistical Challenges & Opportunities (cont.)

### Estimands in Virtual Trials

- Intercurrent events (ICEs )associated with technology use: Implications for future clinical practice
  - Treatment policy: ICEs irrelevant?
  - Composite strategies: ICEs part of definition of outcome variable?
  - While-on-treatment strategy: Loss to follow-up vs. missing data due to device malfunction?
  - Hypothetical strategy: Treatment effect if ICEs did not occur?
- **Definition of outcomes**: Nonstandard mode and frequency of measurements, e.g., wearables, sensors, etc.

## **Example: Analysis of Wearable Device Data**



Activity patterns over time

# **Other Statistical Challenges & Opportunities (cont.)**

### Analyzing high-dimensional, non-standard data



### **Other Statistical Challenges & Opportunities (Cont.)**

A simple model:

Time varying effect of covariates X(t) and Z(t) on

 $Y_{ij}(t)$  = Measurement for subject i, on day j, at time t

$$Y_{ij}(t) = X_i \beta(t) + Z_i(t) \gamma(t) + e_{ij}(t)$$

Approaches:

- Penalized splines to fit  $\beta(t)$ ,  $\gamma(t)$
- Need to account for functional correlation within subjects
- Inference: Bootstrap

### **Other Statistical Challenges & Opportunities (Cont.)**

General framework: Penalized likelihood estimation:  $L(\eta) + \lambda J(\eta)$ ,

 $L(\eta)$ , -log likelihood; J( $\eta$ ), quadratic "roughness" functional Minimization in space H = { *f*: J(*f*) <  $\infty$  } Typically, H Reproducing Kernel Hilbert Space

- Framework for many ML models, including SVM, LASSO, etc.
- A special case: **Smoothing Spline ANOVA (SSANOVA):**

Example: Cubic smoothing splines:

$$\frac{1}{n}\sum_{k=1}^{n}(Y_{k} - \eta(x_{k})^{2} + \lambda \int_{0}^{1}(\eta''(x))2dx$$
, where

{f: 
$$\int_0^1 (f'(x)) 2dx < \infty$$
 }

Inference relating to SSANOVA: Bayesian confidence/credible intervals

### Statistical Challenges & Opportunities (Cont.)

• Other commonly used techniques for **wearable device** data:

Examples from the literature

- SVM, kNN, CART: Detect various activities (Guiry et al. 2014)
- Random forests, decision Trees, SVM and Naive Bayes:
   Muscle movements (Mortazavi et al. 2014)
- Hidden Markov Models: Categorize epochs into sleep/wake states (Li 2019; detect arm posture Shen et al. 2016)

### Statistical Challenges & Opportunities (Cont.)

#### Inference Involving ML Techniques

- Primary objectives of ML models
  - > Prediction, classification, dimensionality reduction, etc.
  - Most applications not concerned with classical inference: Estimation, testing, confidence interval construction
- Recent developments relating to inference with ML
  - Causal inference in observational studies (Wager 2021; Ratkovic 2019)
  - High dimensional covariate adjustment in RCTs to improve efficiency (Wager et el. <u>2016</u>)
  - Confidence intervals and related inference with random forest (Mentch and Hooker <u>2016</u>; Wager et al. <u>2014</u>)
- Enhancing validity of inference involving high dimensional data
  - > Post-selection inference (Tibshirani et al. 2014)
  - ➤ Targeted learning (van der Laan, <u>2011</u>)
  - > Consider testing as a classification problem (Zhan and Kang, 2019)

# Privacy and Confidentiality: Statistical Considerations

#### Privacy and confidentiality

- Online recruitment may not reliably protect patient against harm
  - Use of sensitive personal information, unintentionally revealed by Internet users
- Measures by data aggregators to protect privacy may be inadequate

#### Recent trends:

- Incorporate privacy constraints in a decision theoretic setting
- Optimality results assessed under local differential privacy: Modelling with privacy data remaining private from statistician or learner

Duchi, Jordan, Martin and Wainwright, 2013. [1302.3203] Local Privacy, Data Processing Inequalities, and Statistical Minimax Rates (arxiv.

### **Data and System Integrity & Other Ethical Issues**

- Implementation of a robust security system
  - Ensure authorized use, identification of authors of records, and availability of audit trails
  - o Authentication of patient identity: AI for biometric authentication
- Best practices to minimize unintentional data corruption during transmission or intentional modification by malicious users.
- Ensure equitable selection of subjects"
  - VTs may exclude those who do not use Internet or own computer/smartphone
  - Bias against the poor, old, or those who live in rural areas.

# **DCTs in Pandemic Settings**

- Pandemic disruptions of traditional trials
  - o Quarantines, site closures, travel limitations, interruptions to drug supply
  - o Covid-19 infections of patients and/or site personnel
- Impacts
  - Informed consent, study visits and procedures, data collection, study monitoring, AE reporting, and changes in site operations
  - o Several clinical trials closed at height of pandelic (Bernstein Research, 2020)
- Mitigating measures
  - Changes in protocol and other operational processes
  - Leverage technology for outcome assessment:
  - Assess analytical approaches: Estimand definitions, combinability of data, etc. (Meyer et al 2020)

# **Concluding Remarks**

- Major issues with current paradigm for drug development
- DCTs can enhance drug development
  - Enhance operational efficiency: Patient recruitment, data capture and processing
- DCTs offer considerable statistical opportunities
  - o Facilitate implementation of complex and innovative designs
  - o Use of modern analytics to analyze high dimensional data
- Success factors
  - o Effective use of technology, and modern analytics
  - Best practices for data and system integrity; and protection of patient privacy and confidentiality
  - Availability of transparent regulatory framework for technology use.

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