Using Recursive Logistic Regression to Develop a Patient-Reported Outcome in Non-Cystic Fibrosis Bronchiectasis

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#### **EMBRACE** Trial

This work is an extension to the trial: Wong, C., et al. *Lancet* (2012) vol. 380, pp. 660–7

Articles

#### Azithromycin for prevention of exacerbations in non-cystic fibrosis bronchiectasis (EMBRACE): a randomised, double-blind, placebo-controlled trial

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#### Summary

Lancet 2012; 380: 660-67 See Comment page 627

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Background Azithromycin is a macrolide antibiotic with anti-inflammatory and immunomodulatory properties. We tested the hypothesis that azithromycin would eccrease the frequency of exacerbations, increase lung function, and improve health-related quality of life in patients with non-cystic fibrosis bronchiectasis.

Methods We undertook a randomised, double-blind, placebo-controlled trial at three centres in New Zealand. Between Feb 12, 2008, and Oct 15, 2009, we enrolled patients who were 18 years or older, had had at least one pulmonary exacerbation requiring antibiotic treatment in the past year, and had a diagnosis of bronchiectasis defined by highresolution CT scan. We randomly assigned patients to receive 500 mg azithromycin or placebo three times a week for 6 months in a 1:1 ratio, with a permuted block size of six and sequential assignment stratified by centre. Participants, research assistants, and investigators were masked to treatment allocation. The coprimary endpoints were rate of event-based exacerbations in the Gromoth treatment period, change in forced expiratory volume in 1 s (FEV) before bronchodilation, and change in total score on S1 George's respiratory questionnaire (SGRQ). Analyses were by intention to treat. This study is registered with the Australian New Zealand Clinical Triak Registry. number ACTRNIE007000641493.

Findings 71 patients were in the azithromycin group and 70 in the placebo group. The rate of event-based exacerbations was 0.59 per patient in the azithromycin group and 1.57 per patient in the placebo group in the 6-month treatment period (rate ratio 0.38, 95% Cl 0.26-0.54; pc0-0001). Prebronchodilator FEV, did not change from baseline in the

# **Bronchiectasis**



- Respiratory condition.
- Caused by chronic infection of airways.
- Signs and symptoms:
  - chronic inflammation of airways
  - bacterial infection
  - recurring exacerbations
  - increased mortality.
  - disabling cough
  - production of large quantities of sputum
  - reduced quality of life.

# **EMBRACE** Design

Objectives Assess the effect of *azithromycin* on health-related quality of life and lung function in patients 18–80 years with bronchiectasis (diagnosed by CT scan).

- Design Multicenter (3), double-blind, placebo-controlled, parallel group (1:1), 141 pts total.
- Intervention 500mg azithromycin capsule vs. placebo, 3 days per week, for 6 months.

Follow-up 6 months (treatment period) and 12 months.

- 1° Endpoints i) Rate of Event Based Exacerbations (EBEs) over 6 mo. treatment period;
  ii) Change in St. George's Respiratory Questionnaire (tot. score); (+ others).
- 2° Endpoints Symptom scores for: sputum purulence, sputum volume, dyspnoea; (+ *others*).

# **Exacerbations**

- Exacerbations and symptom scores recorded prospectively in patient diaries.
- ▶ Each patient-day judged *exacerbation* or *no exacerbation*.
- Key symptoms of an exacerbation are
  - Sputum volume
  - Sputum purulence (colour)
  - Dyspnoea (shortness of breath, coughing).
- ▶ Two types: Event-based (EBE) and Symptom-based (SBE).

#### **EBE** Incidence



Figure : Diarized days by Event-based exacerbations status for each EMBRACE location, all patient-days.

### Exacerbations

#### EBE is Physician-Determined

- EBEs require treatment with antibiotics.
- Ascertainment of EBE requires contact with clinician.

#### SBE is Patient-Determined

- SBEs are adjudicated using daily symptom diaries completed by patients.
- Patients have input into evaluation of their own health status.
- ► This is a patient-reported outcome.

# Manually Adjudicated SBEs (manSBEs)

- Adjudication of SBEs originally done by manual review of diaries.
- > This was laborious and time-consuming.
- Eventually abandoned.

#### Goals

#### Automatically Adjudicate SBEs

- Automatically adjudicate SBEs.
- In the process, revisit the definition  $\Rightarrow$  New SBE.

#### Validate New SBE Against EBE

- Estimate performance of new SBE as a predictor of EBE.
- Assess treatment sensitivity of new SBE.

# (Goals II)

#### Jointly Validate Against Patient-Reported Wellbeing

- Patients also reported their general wellbeing in the diaries.
- Assess, and improve, performance of new SBE as a measure of wellbeing.

# Method

#### Data

- $\blacktriangleright$  Observed  $\sim 50\,000$  patient-days observed on 141 patients across 3 centres over 6 months.
- Symptoms: patients rated severity of
  - Sputum purulence, sputum volume, dyspnoea
  - on a validated 5-point scale, 0 "no symptom"  $\rightarrow$  4 "very much".
- Wellbeing: "I feel well", 1 "strongly agree"  $\rightarrow$  5 "strongly disagree".

# Method

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Symptoms								
Pat.	Day	EBE	SP	SV	DY	Well B	SBE	
1	0	0	1	1	1	1	$\uparrow$	
1	1	1	3	3	4	1	$\uparrow$	
÷	÷	:	÷	÷	÷	÷	Adjudicated	
1	17	1	2	1	5	2	$\downarrow$	
1	18	0	1	0	0	3	$\downarrow$	
÷	÷	÷	:	:	÷	÷	$\downarrow$	

Tab	b	е	ŝ	Examp	le	data
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#### Goal is a Model for Prediction

- Statistical goal is a model to predict a time-ordered, clustered, binary outcome, EBE<sub>i,t</sub>.
- $\blacktriangleright$   $\Rightarrow$  propose a model (somehow!).
- Verify it has good predictive power.

#### **Model Selection**

- Based on manSBE procedure, decided to use symptom scores and EBE at an earlier time-point (EBE<sub>i,t-δ</sub>, 0 < δ) as explanatory variables.
- ▶ Used a GLMM, logit link, with random intercepts for patient.

$$\begin{split} \mathsf{EBE}_{i,t} &\sim \mathsf{Bern}\big(p_{i,t}\big)\\ \mathsf{logit}\, p_{i,t} \,|\, \big(\mathbf{x}, b_i\big) = \mathbf{x}_{i,t}' \boldsymbol{\beta} + b_i\\ b_i &\sim \mathsf{Normal}(0, \tau^2) \end{split}$$

 x<sub>i,t</sub> contains symptom scores averaged over two time windows (contemporaneous, earlier), and EBE<sub>i,t-δ</sub>:

$$\mathbf{x}_{i,t}' = \begin{bmatrix} 1 & \overline{\mathsf{SV}}_{i,\mathsf{cont.}} & \overline{\mathsf{SP}}_{i,\mathsf{cont.}} & \overline{\mathsf{DY}}_{i,\mathsf{cont.}} \\ & \overline{\mathsf{SV}}_{i,\mathsf{earl.}} & \overline{\mathsf{SP}}_{i,\mathsf{earl.}} & \overline{\mathsf{DY}}_{i,\mathsf{earl.}} & \mathsf{EBE}_{i,t-\delta} \end{bmatrix}$$

#### **Model Selection**

Dichotomize using a threshold, c, such that sensitivity = specificity:

$$\mathsf{SBE} \equiv \widehat{\mathsf{EBE}}_{i,t} = \begin{cases} 1 & \text{if } \widehat{p}_{i,t} > c \\ 0 & \text{if } \widehat{p}_{i,t} \le c \end{cases}$$

#### Design parameters are: **x**, $\delta$ , *c*.

- x,  $\delta$  Time windows, averaging method, EBE offset chosen to give good in-sample predictive performance (using AUC).  $\delta=5$ 
  - *c* Two-stage estimation of *c*.

# **Model Performance**

#### Two-fold Cross-validation

- > Split data into a training set and a hold-out set for validation.
- Randomly select 70 percent of the patients and allocate all their observations to the training set.
- > The remainder go into the hold-out set.

#### **Prospective Prediction**

 The selected model is retrospective in that today's prediction depends on earlier GP-adjudicated EBEs.

$$\operatorname{logit} p_{i,t} | \left( \mathsf{EBE}_{i,t-5}, \cdot \right) = \mathbf{x}'_i \beta + b_i \tag{1}$$

► We want a prospective model based on patient-reported outcomes ⇒ must use its own earlier predictions.

logit 
$$p_{i,t} \mid \left(\widehat{\mathsf{EBE}}_{i,t-5}, \cdot\right) = \mathbf{z}'_i \beta + b_i$$
 (2)

- ▶ (1) is a *recursive logistic* model (Bonney, 1986, 1987).
- ▶ To fit (2), a sequential procedure was used.

# Sequential Approach

1. Initialize by generating retrospective predictions,  $\widehat{\mathsf{EBE}}_{i,1}^{[\mathsf{ret}]}$ , ...,  $\widehat{\mathsf{EBE}}_{i,5}^{[\mathsf{ret}]}$ , using  $\widehat{\beta}$  and threshold,  $c^{[\mathsf{ret}]}$ , from the retrospective model.

#### Using the training set:

- 2. Sequentially generate prospective predictions  $\widehat{\mathsf{EBE}}_{i,6}^{[\mathsf{pro}]}$ ,  $\widehat{\mathsf{EBE}}_{i,7}^{[\mathsf{pro}]}$ , ....
  - Use "population level" predictions
  - ► Use c<sup>[ret]</sup> to threshold the predicted probabilities (we have to because this is the only c currently available).
- 3. Re-estimate the binary threshold  $\rightarrow c^{[pro]}$ .

#### Using the hold-out set:

4. Repeat 2 using  $c^{[pro]}$ .

# **Method Overview**

- 1. Build a **retrospective** prediction model for  $EBE_t$  using
  - symptom scores
  - GP-adjudicated EBE status at times  $t \in [t \delta, t_0)$ .
- 2. Convert to a "prospective" model for  $EBE_t$  using
  - retrospective design
  - ▶ patient-report-derived EBE status at times  $t \in [t \delta, t_0)$ .
- 3. Estimate its predictive performance.

Dataset	Model	c (used)	c (Opt.)	Sens. (%)	Spec. (%)
Training	Retro.	0.093	0.093	90	92

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Training	Retro.	0.093	0.093	90	92
	Prosp.	0.093	0.048	76	88
	Prosp.	0.048	0.048	83	83
Hold-out	Prosp.	0.048	_	90	79

- Our prospective SBE predictor,
  - misses 10 percent of the EBEs (1 in 10)
  - calls an EBE 21 percent of time there isn't one (1 in 5).
- Relative to using the whole dataset,
  - Estimated sensitivity equal,
  - ► Specificity is 86 percent (↓ 13 percentage points).

# **Patient-Reported Wellbeing**

▶ Patients also reported wellbeing each day using a 1–5 scale.

DIARY CARD	Subject In	litials	Subject No		
Study week nu	mber: 🗌 🗌	]			
Wellbeing I feel well	1 Strongly agree	2 Agree	3 Neither agree nor disagree	4 Disagree	5 Strongly disagree
		<b>0</b> .	1 <b>0</b> .	1	E

- Ultimately, we're interested in a patient-reported outcome that is sensitive to both changes in physical state and patient-reported wellbeing.
- How is our new definition of SBE associated with wellbeing?
- Do we get "closer" to wellbeing with SBE rel. to EBE?

#### Wellbeing and SBE

Linear predictor, WB, EBE Subject Number=101



# Wellbeing and SBE

Linear predictor, WB, EBE

Subject Number=147



Figure : Wellbeing and SBE linear predictor for patient no. 147.

# Wellbeing and SBE

- ▶ Weighted Pearson correlation between wellbeing and the linear predictor from the SBE model is  $\hat{\rho} = 0.33$ .
- Future: combine the SBE prediction model with a similar one for wellbeing.

# Summary

- Exacerbations are an outcome of interest in the study of bronchiectasis.
- Ascertainment of event-based exacerbations (EBEs) requires clinical assessment.
- Symptom-based exacerbations (SBEs) are ascertained from patient-reported symptom scores and exacerbation history, coded "by hand".
- We used logistic regression to develop an "automatic" coding scheme; changes in symptoms that are associated with changes in physical state (EBE).
- As a classifier of EBE the performance was quite good (sens. 90%, spec. 79%).

# **Bibliography**

- Bonney, G. E. (1986). Regressive Logistic Models for Familial Disease and Other Binary Traits. *Biometrics*, 42(3):611–625.
- Bonney, G. E. (1987). Logistic Regression for Dependent Binary Observations. *Biometrics*, 43(4):951–973.
- Wong, C., Jayaram, L., Karalus, N., Eaton, T., Tong, C., Hockey, H., Milne, D., Fergusson, W., Tuffery, C., Sexton, P., Storey, L., and Ashton, T. (2012). Azithromycin for Prevention of Exacerbations in Non-Cystic Fibrosis Bronchiectasis (EMBRACE): a Randomised, Double-Blind, Placebo-Controlled Trial. *The Lancet*, 380(9842):660–7.