

Jackson Burton¹, Daniela J Conrado¹, Brian Corrigan², Timothy Nicholas², Danny Chen², Julie Stone³, Vikram Sinha³, Brian Willis⁴, Wenping Wang⁵, Volker D. Kern¹, Stephen P Arnerić¹, Klaus Romero¹ on behalf of the Coalition Against Major Diseases
¹Critical Path Institute, Tucson, AZ; ²Pfizer, Groton, CT, USA; ³Merck, North Wales, PA, USA; ⁴Eli Lilly, Indianapolis, ID, USA; ⁵Novartis, East Hanover, NJ, USA

Background

- The Coalition Against Major Diseases (CAMD), a public-private partnership, previously developed a regulatory-endorsed (FDA (1) & EMA) clinical trial simulation tool (CTS) for Alzheimer's disease (AD), using integrated standardized data from control arms of legacy trials in mild to moderate AD
- Contemporary datasets acquired within CAMD after the initial regulatory endorsement warrant an update of the CTS

Objectives

- Acquire, standardize, and integrate contemporary patient-level datasets into the CAMD database according to the Clinical Data Interchange Standards Consortium (CDISC) standards
- Utilize expanded database to update the existing CTS for mild-to-moderate AD using a Bayesian mixed effects modeling framework

Methods

Data Sharing Initiative (Figure 1):

- Consortia, such as CAMD, are initiated by collaborating with stakeholders to address an unmet medical need
- Research questions are framed and data sources are identified.
- Acquisition of relevant data sets from data contributors is initiated with a legally binding data contribution agreement
- An encrypted transfer is used to send data to a secure storage server
- A comprehensive data remapping effort to CDISC standards is performed in conjunction with a thorough data curation
- Standardized data sets are integrated into the consortium database.

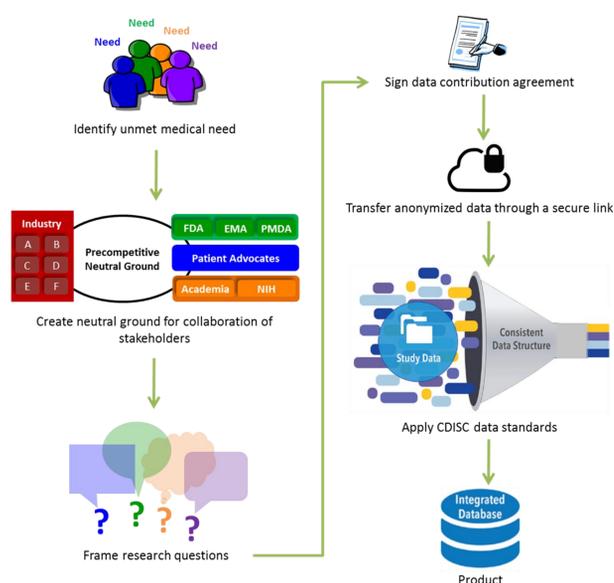


Figure 1. Schematic of an expanded data sharing initiative such as CAMD

Source: DJ Conrado, MO Karlsson, K Romero, C Sarrac, JJ Wilkins. Open Innovation: towards sharing of data, models and workflows. Eur J Pharm Sci. 2017 [epub ahead of print]

Preliminary update of the CTS:

- Compared to the original CTS tool, modifications and additional aspects to be investigated include:
 - Use of patient-level data exclusively
 - Bayesian framework using the Hamiltonian Monte Carlo method to estimate the posterior
 - Investigate an additive allele effect for APOE4
 - Include stable background medication as a covariate
 - Use of a generalized logistic regression mixed effects approach following the framework of Conrado et al. (2) to describe the nonlinear natural progression of AD measured by the ADAScog11 scale :

$$ADAScog(t) = \frac{70 \cdot ADAScog_0}{\left[ADAScog_0^\beta + (70^\beta - ADAScog_0^\beta) e^{-\beta r t} \right]^{1/\beta}}$$

- Random effects on baseline $ADAScog_0$ and rate of progression r
- Beta distributed residual variability to ensure predictions of ADAScog11 are bounded
- Covariates: age, gender, number of APOE4 alleles, and concomitant medication use

Results

Expanded database overview :

- The contemporary CAMD database contains 15 studies of control data from legacy trials, an increase of 6 studies since the development of the original CTS (Table 1)

Table 1 Summary level statistics comparing original and contemporary CAMD database

Variable	Original database	Expanded database
Number of studies	9	15
Individuals	3255	4575
Mean age	73.9	74.1
% female	55.1%	55.4%
Mean years since dX	2.07	2.46
Mean baseline ADAScog11	23.4	24.0
Info on number of APOE4 alleles	1486	1895
Concomitant medication info	2483	3271

Preliminary Results on the CTS Update

- The observed temporal trajectory of ADAScog11 in control arm individuals and mean predicted progression are in Figure 2

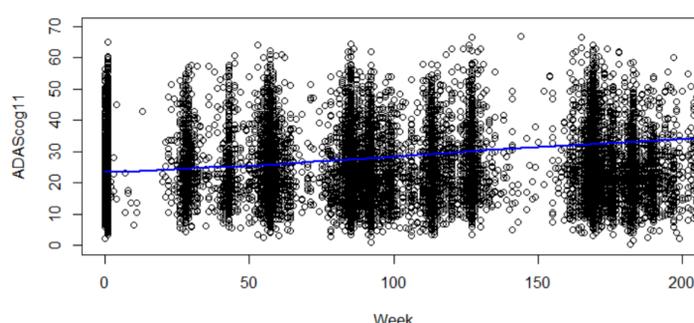


Figure 2 Observed ADAScog11 trajectories (dots) and predicted mean trajectory (blue line)

- The estimated parameters, including progression rate, covariate effects, and between subject variability are shown in Table 2.

Table 2 Parameter estimates for natural progression of AD measured by ADAScog11

Parameter	Description	Estimate	95% CI
$\theta_{baseline}$	Population mean baseline score	21.4	(19.8, 23.2)
θ_{rate} (year ⁻¹)	Population mean progression rate	0.145	(0.072, 0.22)
θ_{age}	Effect of age of progression rate	-0.025	(-0.049, -0.013)
θ_{sex}	Effect of sex on baseline	0.003	(8e-5, 0.011)
θ_{ApoE4_b}	Effect of number of ApoE4 alleles on baseline	0.034	(0.009, 0.062)
θ_{ApoE4_r}	Effect of number of ApoE4 alleles on rate	0.204	(0.066, 0.411)
θ_{comed}	Effect of stable background medication on rate	-0.41	(-0.75, -0.22)
$\omega_{patient_b}^2$	Variance of inter-individual variability on baseline	0.411	(0.402, 0.420)
$\omega_{patient_r}^2$	Variance of inter-individual variability on rate	0.202	(0.194, 0.211)

- Estimated population baseline severity and rate of progression are in good agreement with previous studies (2),(3)
- Note worthy results indicate an additive allele effect for APOE4 that correlates with increased rate of progression and stable medication use correlating with faster rate of progression

Envisioned outcome

- A completed update of the CTS will involve the following milestones:
 - Separation of natural progression and placebo effect component by incorporating observational longitudinal data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database
 - Confirm the additive allele effect of APOE4 and background medication use related finding with the ADNI data
 - Develop a user-friendly interface to provide accessibility of the tool to all members of a clinical development team
- Regulatory endorsement for the updated CTS will be pursued in order to provide the most up to date tool for clinical trial design and simulation for mild to moderate AD.

References:

- Research C for DE and. Development & Approval Process (Drugs) - Drug Development Tools: Fit-for-Purpose Initiative [Internet]. [cited 2017 Sep 8]. Available from: <https://www.fda.gov/drugs/developmentapproval-process/ucm505485.htm>
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