

Collaborative research in risk prediction

Thomas Debray, PhD

Julius Center for Health Sciences and Primary Care, University Medical Center Utrecht, The Netherlands

Cochrane Netherlands, Utrecht, The Netherlands

thomasdebray.be

Aims of my talk

- To describe the value of clinical prediction models
- To foster interdisciplinary collaboration
- To highlight the merits of data sharing
- To inspire you



Who am I?

Current position

- Assistant Professor, Julius Center for Health Sciences and Primary Care
- Affiliated Researcher, Cochrane Netherlands
- Honorary Senior Research Associate, University College London
- Honorary Departmental Senior Research Fellow, University of Oxford

Background in

- Computer Science (BSc) ■
- Artificial Intelligence (MSc) =
- Epidemiology (MSc, PhD) **=**



What is risk prediction?

Estimating the probability of something that is yet unknown

- Presence of a certain disease \rightarrow diagnosis
- Future occurrence of a particular event \rightarrow prognosis



How do we predict?

Combine information from multiple predictors

- Subject characteristics (e.g. age, gender)
- History and physical examination results (e.g. blood pressure)
- Imaging results (e.g. computed tomography scan)
- (Bio)markers (e.g. coronary plaque)



Why do we predict?

- To inform patients and their families
- To decide upon further testing (e.g. magnetic resonance imaging)
- To decide upon patient referral (e.g. to secondary care)
- To decide on preemptive or therapeutic strategies
- To guide treatment decisions







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Risk prediction - the reality

Many prediction models perform more poorly than anticipated, do not affect clinical practice, or are implemented for the wrong reasons

- Small & poor quality studies
- · Limited variation in studied patients, settings or populations
- · Lack of validity and effectiveness assessments





The rise of "big" data sets



The rise of "big" data sets

Data increasingly available for thousands or even millions of patients from multiple practices, hospitals, or countries.

- Analyses of databases and registry data containing e-health records
- Meta-analysis of individual participant data from multiple studies

A common theme in these data is the presence of clustering, which allows to study generalizability of model predictions across different settings and populations



Exemplar projects

A selection of ongoing collaborative projects using "big" data sets

- Identification of patients in need of specialized trauma care
- Prognosis for patients with amyotrophic lateral sclerosis
 Image: Im
- Personalized medicine for infectious diseases





Identification of patients in need of specialized trauma care

Prehospital trauma triage is essential to get the right patient to the right hospital

- Need for prehospital triage tool(s)
- Many existing tools have poor discrimination
- · Most studies are based on small and local data sets
- Limited time and equipment to collect patient data on-scene





Identification of patients in need of specialized trauma care

The Trauma Triage App (TTApp)

- Mobile application
- Logistic regression model to estimate the need of specialized trauma care
- Based on data from a single Emergency Medical Service (EMS)

Improvements are underway

- Combine data from multiple EMS regions in the Netherlands
- Adopt machine learning methods (XGBoost)
- Investigate variation in prediction performance across NL regions

ALS

- Neurodegenerative disease
- No cure or effective treatment
- Heterogeneous survival (several months to > 10 years)
- Prof. Stephen W Hawking
 - Diagnosed with ALS in 1963
 - Life expectancy upon diagnosis: 2 years
 - Died on March 14, 2018 (aged 76)



Need for accurate tools that can predict survival in patients diagnosed with ALS

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We set up an international collaboration between neurologists, epidemiologists and statisticians

- To combine cohort data
 - from 11,475 patients
 - from 14 ALS centres across Europe
- To implement recently developed statistical methodology
 - ▶ for dealing with missing values in large, clustered, data sets
 - ▶ for assessing prediction model performance across different ALS centres
- To publish a prediction model that is freely accessible by medical doctors
 - to provide estimates of prognosis in individual patients with ALS
 - ▶ to facilitate clinical practice and innovative trial design

We externally validated the prediction model in each of the 14 ALS centres (probability of "good" performance in new centres: 98%)

A		В	
Validation cohort	c statistic (95% CI)	Validation cohort	Calibration slope (95% CI)
Utrecht, Netherlands -	0.79 (0.77 to 0.81)	Utrecht, Netherlands -	1·12 (1·05 to 1·19)
Dublin, Ireland —	0-78 (0-76 to 0-80)	Dublin, Ireland —	0.96 (0.87 to 1.04)
Torino, Italy	0.77 (0.75 to 0.79)	Torino, Italy —	0.96 (0.87 to 1.04)
Sheffield, UK	0.78 (0.76 to 0.80)	Sheffield, UK —	0.99 (0.90 to 1.08)
London, UK	0-82 (0-79 to 0-84)	London, UK	1.09 (0.96 to 1.21)
Oxford, UK	0.78 (0.75 to 0.81)	Oxford, UK	0.99 (0.85 to 1.12)
Leuven, Belgium	0.77 (0.75 to 0.80)	Leuven, Belgium	0.96 (0.84 to 1.08)
Lisbon, Portugal	0-77 (0-74 to 0-80)	Lisbon, Portugal	0.95 (0.82 to 1.08)
Hannover, Germany	0-74 (0-71 to 0-77)	Hannover, Germany	0.83 (0.70 to 0.96)
Ulm, Germany	- 0-83 (0-78 to 0-88)	Ulm, Germany	1.17 (0.95 to 1.39)
Jena, Germany	0-80 (0-75 to 0-85)	Jena, Germany	1.12 (0.90 to 1.34)
St Gallen, Switzerland	0-80 (0-74 to 0-86)	St Gallen, Switzerland	1.01 (0.80 to 1.22)
Tours, France	0.76 (0.71 to 0.81)	Tours, France	1.09 (0.88 to 1.31)
Limoges, France	0-80 (0-73 to 0-86)	Limoges, France	1.07 (0.82 to 1.32)
Meta-analysis	0-78 (0-77 to 0-80)	Meta-analysis	1.01 (0.95 to 1.07)
0.70 0.75 0.80 0.85	0.90 95% PI 0.74 to 0.82	0.60 0.80 1.00 1.2	95% PI 0-83 to 1-18
c statistic Miscalibration Miscalibration		bration	

Utrecht, Oct 25, 2018

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Collaborative research in risk prediction



The life expectancy of Stephen Hawking

- Predicted 10-year survival probability: 94%
- Primary endpoint reached after 22 years
- Young age of onset was the most important factor for his long survival





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Prognosis for patients with amyotrophic lateral sclerosis: development and validation of a personalised prediction model

Henk- Jan Westeneng, Thomas P.A. Debray, Anne E.Visser, Ruben P.A.van Eijk, James P.K.Rooney, Andrea Calvo, Sarah Martin, Christenber (McDematt Alexander & Thomsson, Susana Rato, Yonia Kabelaus, Anaela Basenbahm, Besteire Stubandarff, Halma Sammer Bas M Middelkoop, Annelot M Dekker, Joke J F A van Vuat, Wouter van Rheenen, Alice Vaida, Mark Heverin, Mbarnhe Kazoka, Hannah Hollinger, Marta Gromicho, Soria Körner, Thomas M Ringer, Annekathrin Rödiger, Anne Gunkel, Christopher E Shaw, Annelien L Bredenoord Michael A van Es, Philippe Corria, Philippe Countier, Markus Weber, Julian Grosskerutz, Albert C Ludalah, Susanne Petri, Marnede de Couvalho, Philip Van Domme: Kevin Talhet, Martin R Tumer, Pomela I Shaw, Amenar Al-Chalabi, Advisoro Chiù, Orle Hardiman, Kavel G M Mosen-Jan H Veldink, Leonard H van den Berg

The life expectancy of Stephen Hawking. according to the ENCALS model

Correspondence

Stephen W Hawking, one of the most

in some cases³⁴ We have examined the endpoint was reached because he Professor Hawking's clinical phenotype had a tracheostomy. Then, the model using our recently validated predictive predicts that he had a 20% probability model of survival (the ENCALS survival of surviving, to the time of his death model), which is based on eight some 33 years later. According to the predictors.) The model was designed to ENCALS survival model. Professor generate survival probabilities on the Hawking's young age of onset was famous physicists, died on March 14. basis of a composite endpoint, which the most important factor for his 2018, at the age of 76 years. Although we defined as death, tracheostomy, long survival. However, more than he was best known for his remarkable or dependency on non-invasive venti- half of his disease duration (ie after

and supplied can be exceptionally long. 1985, which is within this interval

10.1016/S1474-4422(18)30089-9 10.1016/S1474-4422(18)30241-2

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Personalized medicine for infectious diseases

Main challenges to manage, exchange and preserve research data efficiently

- Separate storage of research data hampers both within- and cross-study scientific advancement
- Density of generated data often exceeds the storage capacity of typical databases
- · Lack of resources for integrated data analysis across cohorts
- Governance of sample- and data sharing is complicated
- Utility of OMICS data disproportionally affect countries in the global South.

Personalized medicine approaches hold tremendous promise for improving the detection of infectious diseases and for developing targeted treatment strategies.

Personalized medicine for infectious diseases

Horizon 2020 project of 6 mln EUR

- To develop an integrated sustainable platform for collating data within and across infectious disease cohorts
- To develop innovative solutions for shared ownership, linked data and biorepositories
- To develop and evaluate statistical methods for collaborative analysis (Utrecht)

Collaboration with physicians, virologists, micro-biologists, epidemiologists, bio-informaticians, bio-statisticians, ethicists, and many more



Final thoughts

Big collaborative projects are increasingly important

- To improve the quality and reproducibility of research
- To address more complex questions
- To provide more generalizable answers
- To enhance impact of research findings

Funding organizations play an important role to identify and finance critical expertise. Academic institutions need to train scientists and foster their creativity.