AMS-JSPS-AMED Joint Symposium on Data-Driven Health:

Session 3: Health data for clinical decision-making

Chair: Professor Toru Suzuki

Aims: To examine how health data might inform machine learning and artificial intelligence solutions to improve clinical care, taking account of the ethical and regulatory considerations, challenges, opportunities, and pathways to implementation for this technology.

14.30 – 14.45	Provisional title: **Health data applications in clinical care** Professor Masao Iwagami, Tsukuba University
14.45 – 15.00	Provisional title: **Using machine learning and clinical AI to improve patient care** Professor David Clifton
15.00 – 15.15	Provisional title: **Ethics and regulatory policy for advanced health technologies** Dr Tamami Fukushi, AMED
15.15 – 15.45	**Session 3 panel discussion**

Title: Health data applications in clinical care
~what can we do using routinely collected data?~

Masao Iwagami, MD, MPH, MSc, PhD

Dept. of Health Services Research, Univ. of Tsukuba, Japan

Dept. of Non-Communicable Disease Epidemiology,
London School of Hygiene and Tropical Medicine, UK

Agenda:

1. Introduction (my experience to date)
2. What can we do using routinely collected health data?
3. My view on predicting individual risk of an outcome

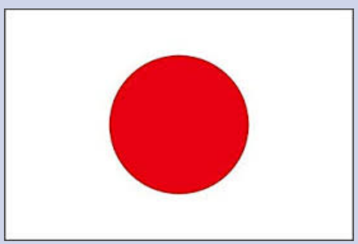
1. Introduction: Masao Iwagami, MD, MPH, MSc, PhD

2008	Univ. of Tokyo (MD)
2008-11	Junior and senior residency
2012	Univ. of Tokyo, School of Public Health (MPH)
2013	LSHTM, Epidemiology (MSc)
2014	LSHTM, Epidemiology and Population Health (PhD)
2018-now	LSHTM, Honorary Assistant Professor
2018-now	Univ. of Tsukuba, Assistant Professor

ELECTRONIC HEALTH RECORDS RESEARCH GROUP

1. Introduction: Masao Iwagami, MD, MPH, MSc, PhD

Key words: Routinely collected health data
Acute kidney injury (AKI), Chronic kidney disease (CKD),
Sepsis, Mental health disorders, Pharmacoepidemiology

	Inpatient routinely collected data	Outpatient routinely collected data
	**DPC claims database** ○ MDV medical.data.vision	**NDB claims database** △ JMDC Claims Database
	△ Hospital Episode Statistics (HES)	○ CPRD

2. What can we do using routinely collected data?

(i) To describe burden of a disease

(ii) To examine the association between an exposure and an outcome

(iii) To predict individual risk of an outcome

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ndt NEPHROLOGY DIALYSIS TRANSPLANTATION

Current state of continuous renal replacement therapy for acute kidney injury in Japanese intensive care units in 2011: analysis of a national administrative database

FREE

Masao Iwagami, Hideo Yasunaga, Eisei Noiri, Hiromasa Horiguchi,

Mortality of dialysis AKI = 50.6%

BJGP British Journal of General Practice

Chronic kidney disease and cause-specific hospitalisation: primary and secondary care patient data

Masao Iwagami, Ben Caplin, Liam Smeeth, Laurie A Tomlinson and Dorothea Nitsch

Pts with CKD are hospitalised more often than Pts without CKD for various reasons

Most likely conclusions: More clinical attention, research, and funding are needed for the disease

2. What can we do using routinely collected data?

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Critical Care Medicine

Society of Critical Care Medicine

Postoperative Polymyxin B Hemoperfusion and Mortality in Patients With Abdominal Septic Shock: Propensity-Matched Analysis*

There is no association between endotoxin adsorption and mortality

BJCP British Journal of Clinical Pharmacology

Gastrointestinal bleeding risk of selective serotonin reuptake inhibitors by level of kidney function: A population-based cohort study

There is association between SSRI (antidepressants) and GI bleeding

Most likely conclusion: If the association was causal, modifying the exposure would/wouldn’t improve the outcome

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KAKEN Search Research Projects Search Researchers

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Development of risk prediction model for re-admission in large inpatient data with machine learning

Project/Area Number	19K19430
Research Category	Grant-in-Aid for Early-Career Scientists
Allocation Type	Multi-year Fund
Review Section	Basic Section 58030:Hygiene and public health-related: excluding laboratory approach
Research Institution	University of Tsukuba
Principal Investigator	岩上 将夫 筑波大学, 医学医療系, 助教 (30830228)
Project Period (FY)	**2019-04-01 – 2022-03-31**
Project Status	Granted (Fiscal Year 2019)
Budget Amount *help	**¥4,290,000 (Direct Cost: ¥3,300,000、Indirect Cost: ¥990,000)**

3. My view on predicting individual risk of an outcome

(i) Is it useful?

(ii) Is machine learning better than traditional methods?

(iii) Does better prediction benefit more?

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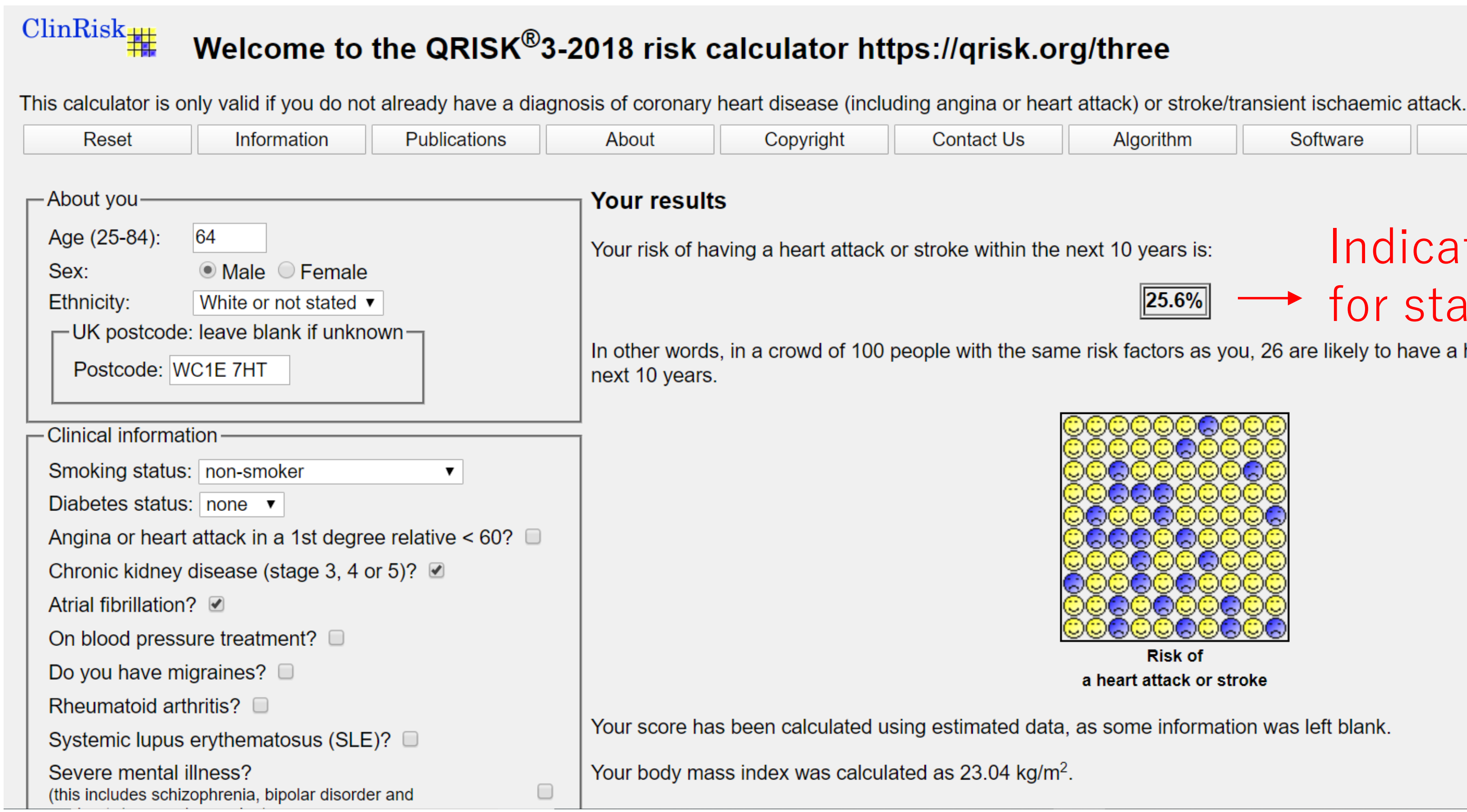

Indication for statin

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糖尿病リスク予測ツール 第2版

Diabetes prediction tool (Japan)

1.基本項目

以下1.～12.は、糖尿病のリスクを予測するための基本項目（必須）です。
数字は半角で入力ください。BMIは自動計算のため入力不要です。

1. ※必須 糖尿病の既往歴 なし ▼
   ※既往とは、医師に診断されたことがある場合です
2. ※必須 性 別 男性 ▼
3. ※必須 年 齢 60 歳
   対象：30～64歳まで
4. ※必須 身 長 170 cm
5. ※必須 体 重 67 kg
6. ※自動算出 BMI 23.2 kg/m²
7. ※必須 腹 囲 80 cm
8. ※必須 タバコを吸っている はい ▼
9. ※必須 最高（収縮期）血圧 147 mmHg
10. ※必須 最低（拡張期）血圧 70 mmHg
11. ※必須 高血圧の薬 なし ▼
12. ※必須 脂質異常症の薬 あり ▼
    ※コレステロール・中性脂肪を下げる薬

Risk of incident DM within 3 years

3年以内に糖尿病を発症するリスク

13.0%

「発症するリスク」とは、職域コホート（J-ECOHスタディ）のデータにより構築された糖尿病のリスク予測モデルから、入力された条件と同等の方が3年以内に糖尿病を発症する確率です。

※ご家族に糖尿病の方がいる場合にはリスクは上記より高くなります。

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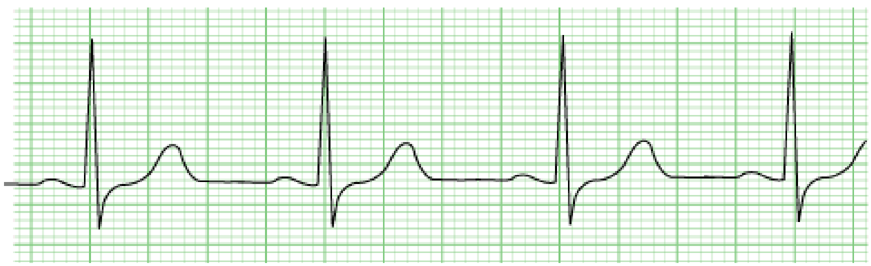

Articles

An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction

Zachi I Attia, Peter A Noseworthy*, Francisco Lopez-Jimenez, Samuel J Asirvatham, Abhishek J Deshmukh, Bernard J Gersh, Rickey E Carter, Xiaoxi Yao, Alejandro A Rabinstein, Brad J Erickson, Suraj Kapa, Paul A Friedman*

Summary

Background Atrial fibrillation is frequently asymptomatic and thus underdetected but is associated with stroke, heart failure, and death. Existing screening methods require prolonged monitoring and are limited by cost and low yield. We aimed to develop a rapid, inexpensive, point-of-care means of identifying patients with atrial fibrillation using machine learning.

Lancet 2019; 394: 861-67

Published Online
August 1, 2019
http://dx.doi.org/10.1016/S0140-6736(19)31721-0

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ELSEVIER

Check for updates

Journal of Clinical Epidemiology

Journal of Clinical Epidemiology 110 (2019) 12–22

REVIEW

A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models

Evangelia Christodoulou[a], Jie Ma[b], Gary S. Collins[b,c], Ewout W. Steyerberg[d], Jan Y. Verbakel[a,e,f], Ben Van Calster[a,d,*]

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[b]Centre for Statistics in Medicine, Nuffield Department of Orthopaedics, Rheumatology and Musculoskeletal Sciences, Botnar Research Centre, University of Oxford, Windmill Road, Oxford, OX3 7LD UK

[c]Oxford University Hospitals NHS Foundation Trust, Oxford, UK

[d]Department of Biomedical Data Sciences, Leiden University Medical Centre, Albinusdreef 2, Leiden, 2333 ZA The Netherlands

[e]Department of Public Health & Primary Care, KU Leuven, Kapucijnenvoer 33J box 7001, Leuven, 3000 Belgium

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What is your plan?	Your current risk of colon cancer = 70%	Your future risk of stroke = 70%
Bad validity Sensitivity = 50% Specificity = 50%	Keep observation	Stop smoking Exercise Decrease BP
Good validity Sensitivity = 95% Specificity = 95%	Resecting colon	Stop smoking Exercise Decrease BP

Key messages from Dr. Masao Iwagami

Routinely-collected health data can be used
(i) To describe burden of a disease
(ii) To examine the association between an exposure and an outcome
(iii) To predict individual risk of an outcome

In the predicting individual risk of an outcome,
(i) Is it useful?
(ii) Is machine learning better than traditional methods?
(iii) Does better prediction benefit more?
The most important is to find when the answers are “yes”.