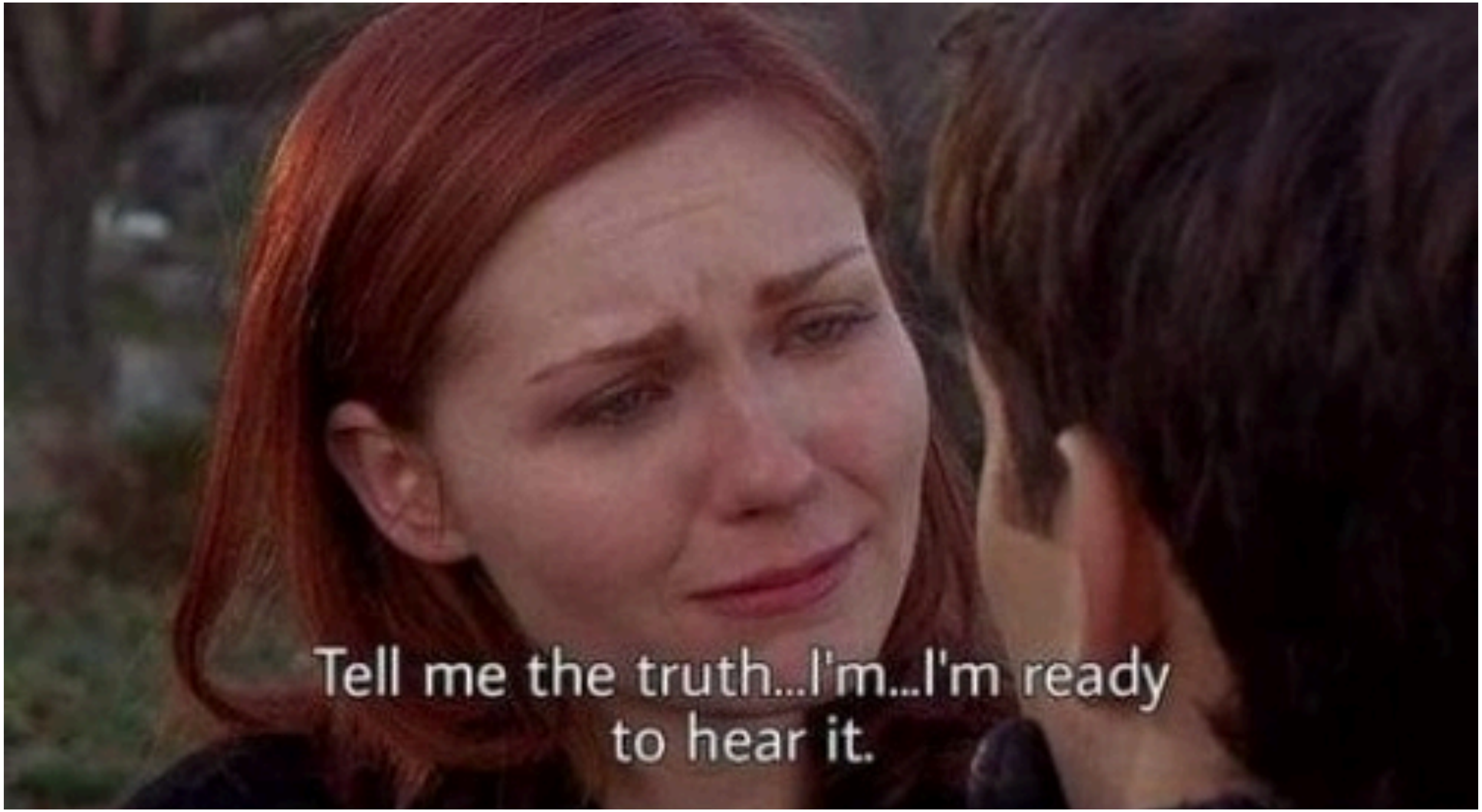
Translation: from research to innovaton

The truth about prediction models



https://twitter.com/MaartenvSmeden/status/1459889566656217092

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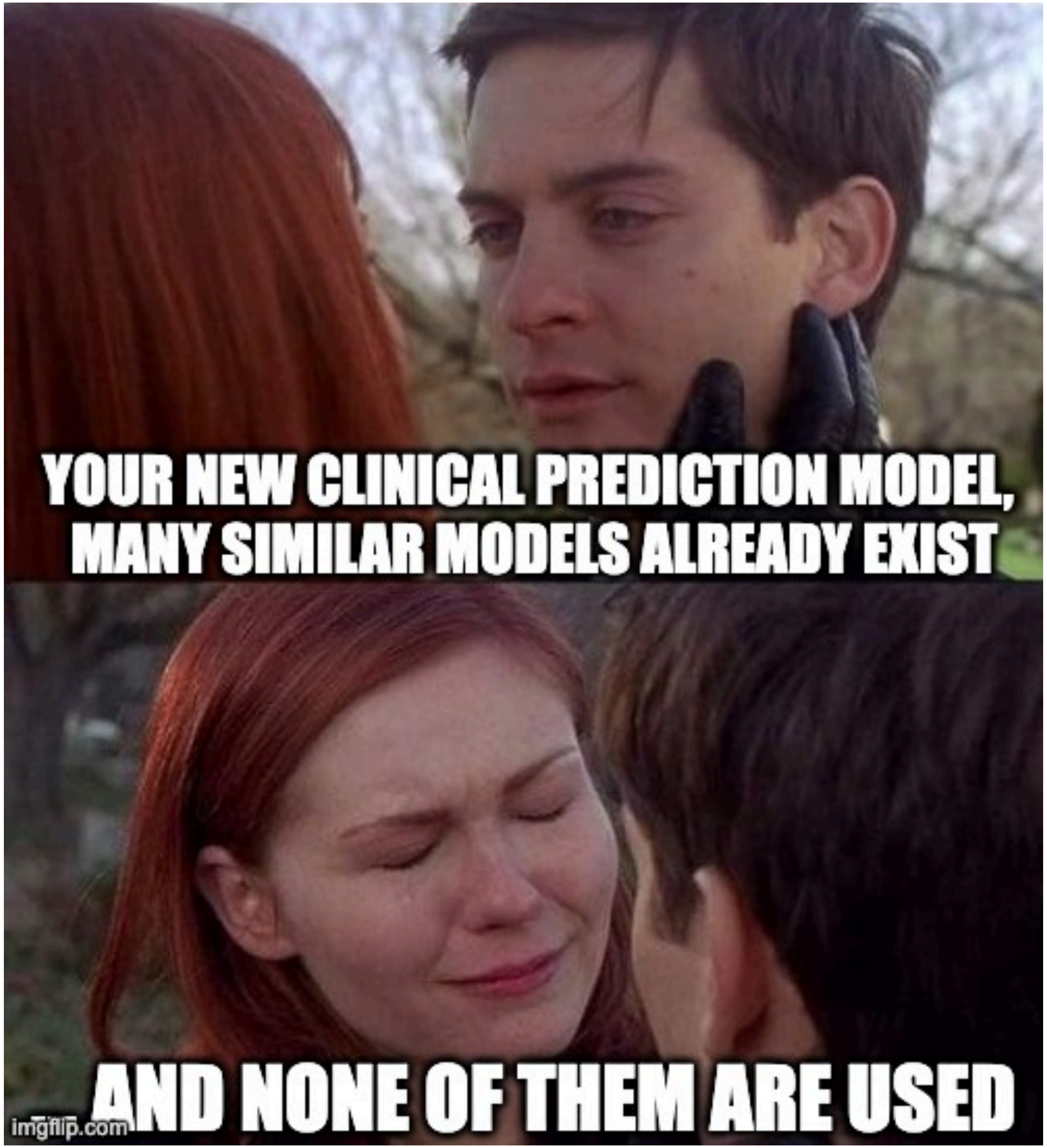
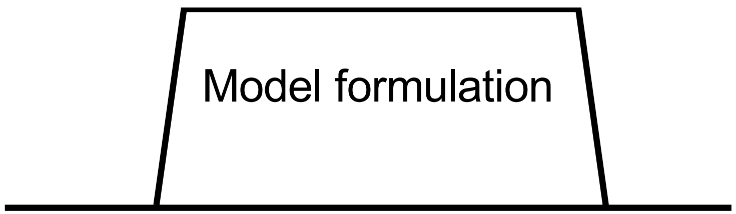


The tower of achievement

Friedman CP, J Am Med Informatics Assoc. 1995;2:65-67.

The tower of achievement



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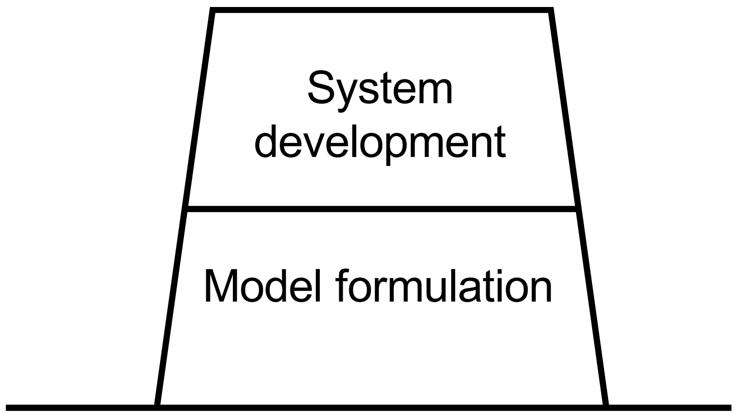

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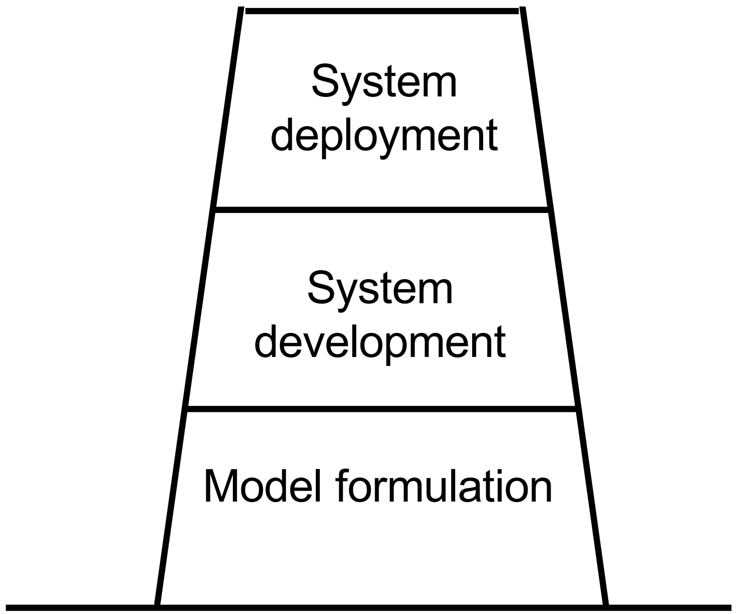

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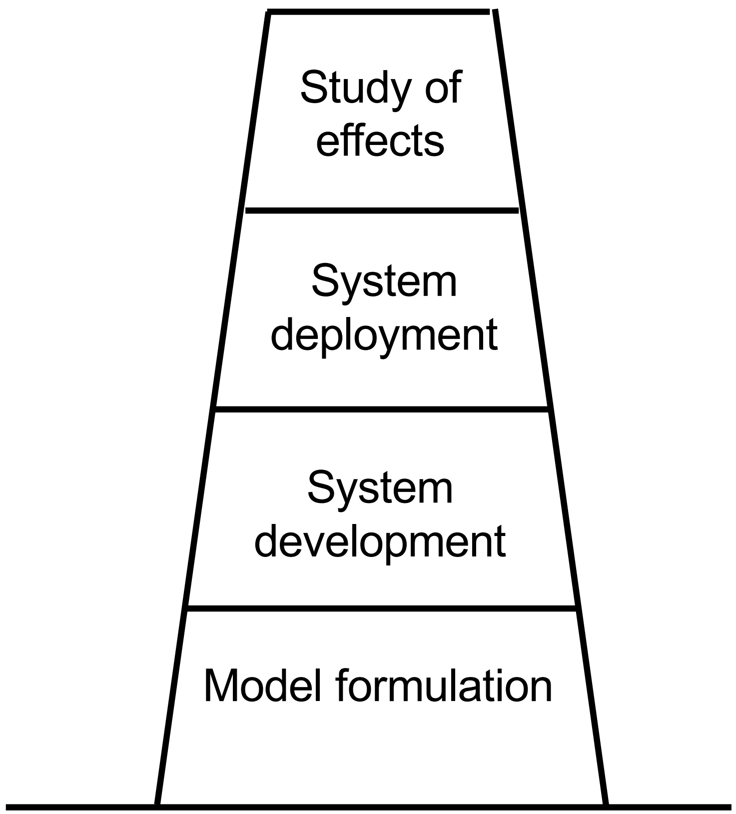

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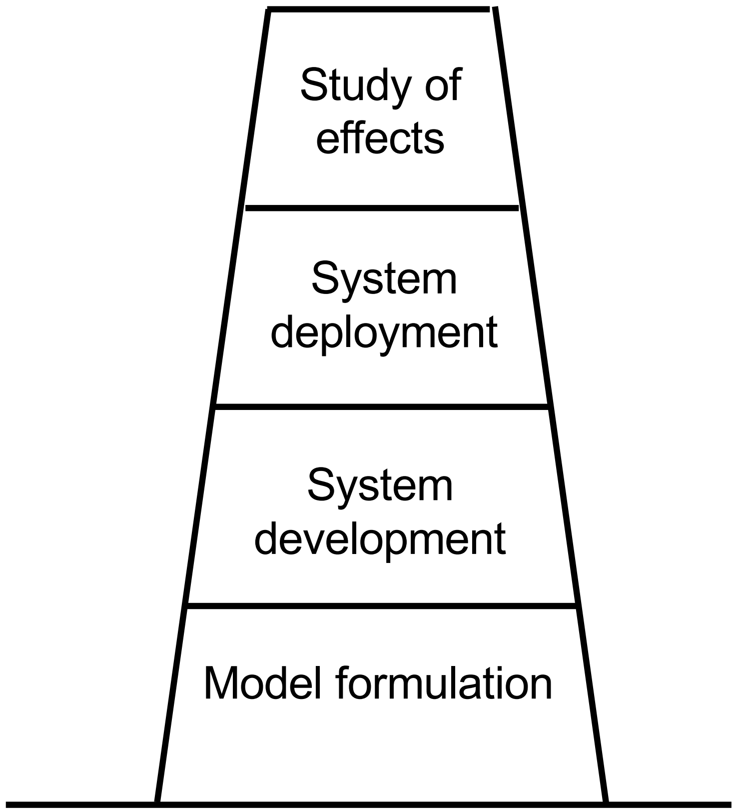
CDSS based on prediction model



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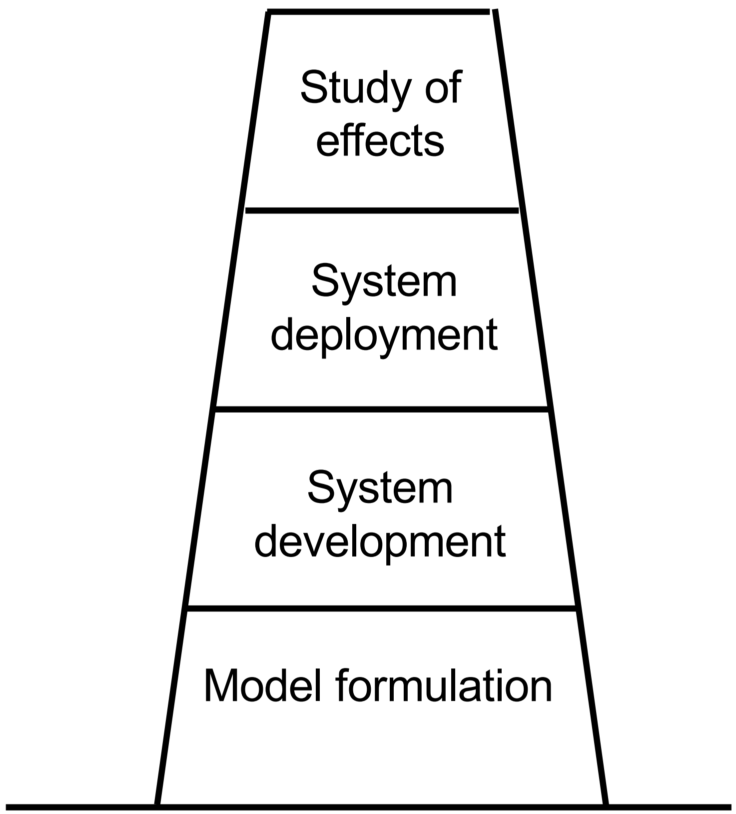

Derive a clinical prediction model from data (using statistical modelling or machine learning)

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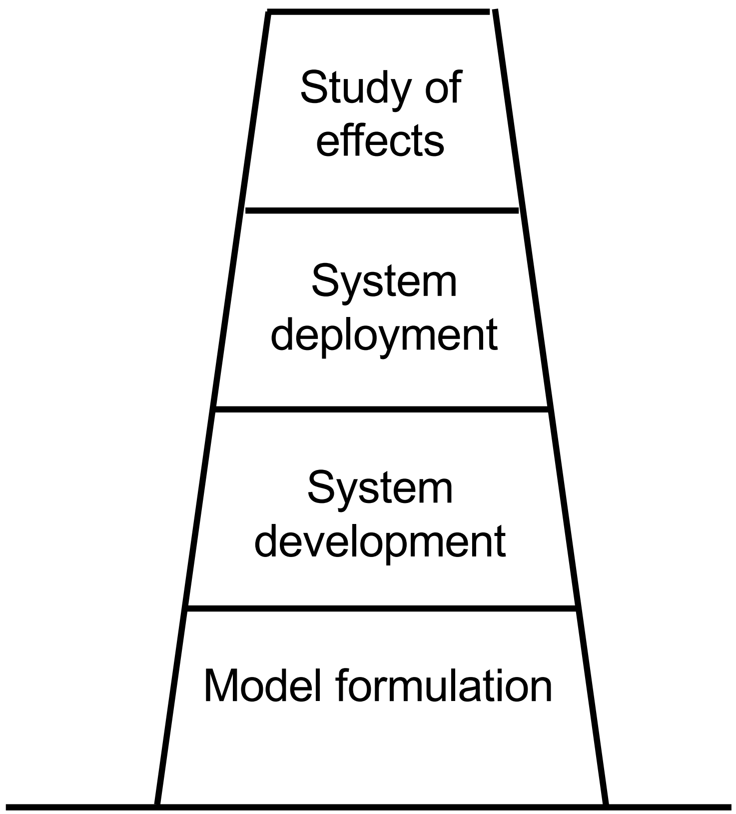

Create software that embeds the model and can be used for decision support in clinical practice

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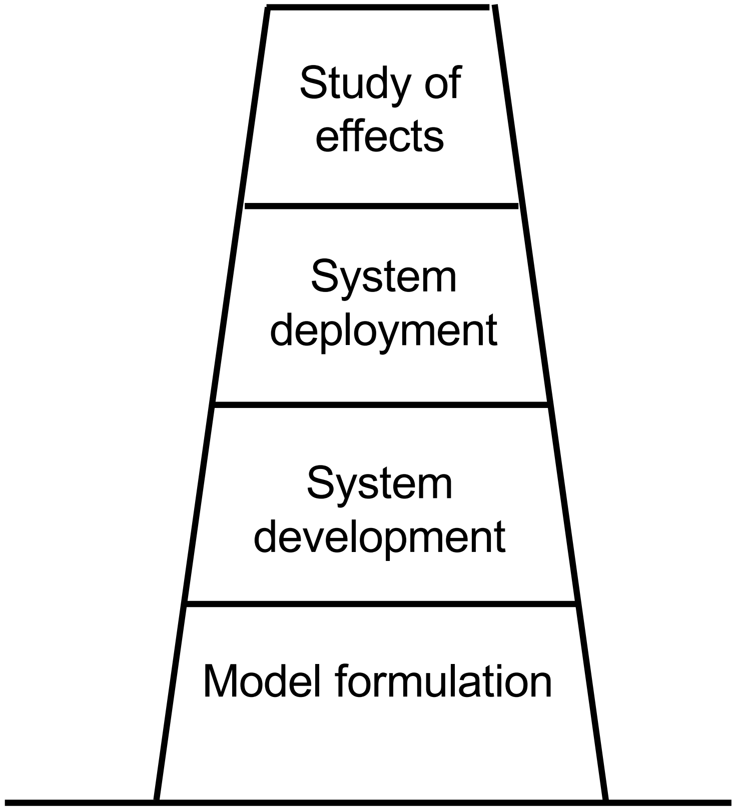

Make the software available to healthcare professionals and give them instructions on how to use it

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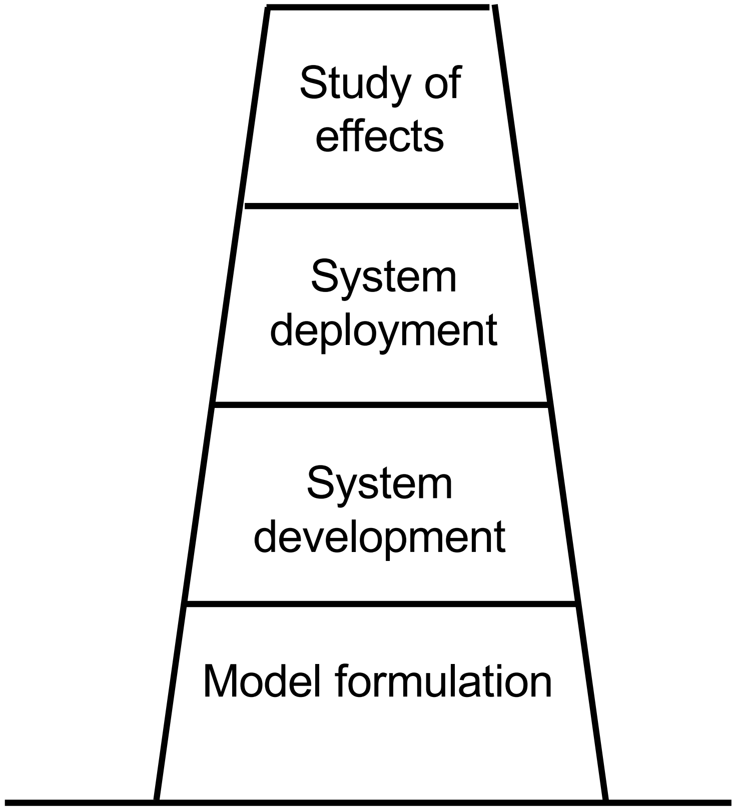

Evaluate whether clinical decisions are affected by the system

Make the software available to healthcare professionals and give them instructions on how to use it

Create software that embeds the model and can be used for decision support in clinical practice

Derive a clinical prediction model from data (using statistical modelling or machine learning)

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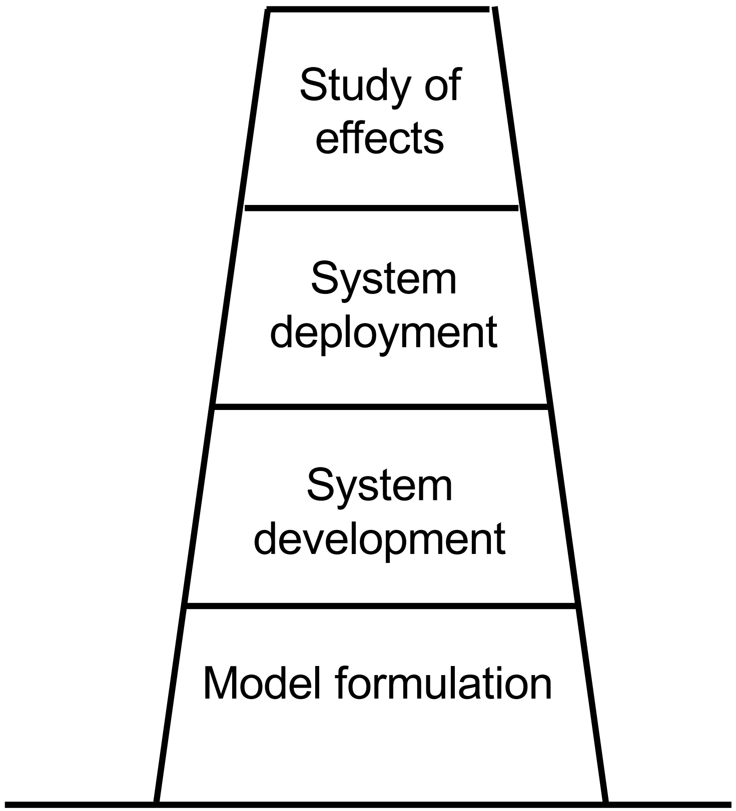
How many systems make it to the top?



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23 models currently recommended by NICE guidelines[1]

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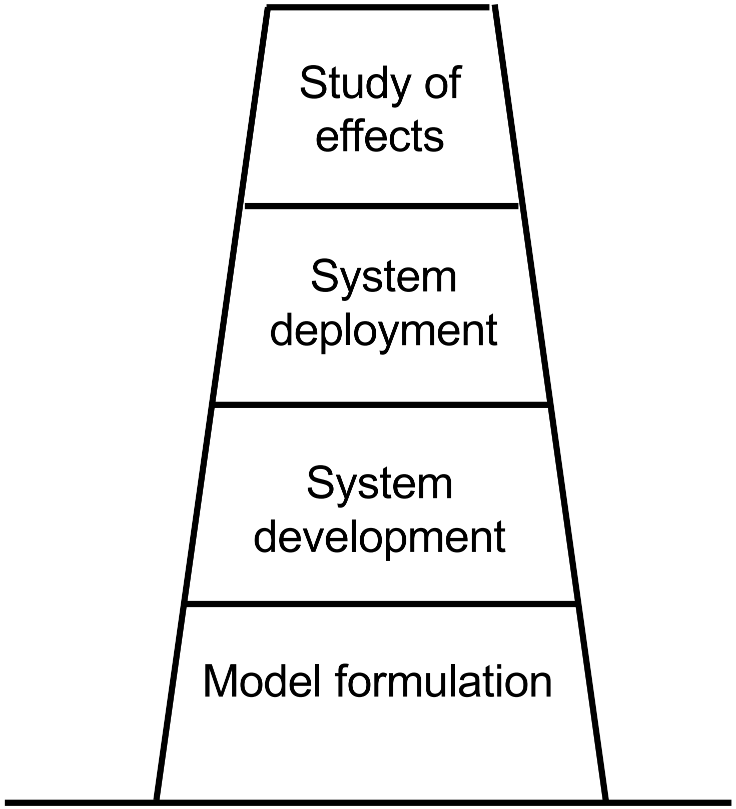
Hundreds of clinical prediction models published in the literature each year (232 for Covid19 alone)

[1] Tsvetanova A et al. J Clin Epidemiol. 2021 Sep 11;140:149-158.

Discussion: Why do so few systems make it to the top?



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Impact of prediction models

- By **impact** of a prediction model we mean the changes that deployment of the model in clinical practice has had on clinical decision making and, ultimately, patient outcomes.
- Many prognostic models have been **validated for predictive accuracy** in external datasets.
- But remarkably few models have been evaluated for impact in clinical practice – there is a huge "**evidence gap**".
- In the cases where it did happen, the results were not always positive.

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Example: Preventing emergency hospital admissions with PRISM

Prism is a web based predictive risk tool that stratifies people into four levels based on their individual risk of an emergency admission to hospital in the following 12 months.

- Risk group 1: 80% of the practice population with the lowest scores
- Risk group 2: the 15% with the next high scores
- Risk group 3: the 4.5% with the next high scores
- Risk group 4: the 0·5% at highest risk of emergency hospital admission

The Prism tool was developed and validated using 300,000 (10% of the Welsh population) anonymised GP and hospital records from which 37 variables with the highest predictive power were selected.

Example: Preventing emergency hospital admissions with PRISM

ORIGINAL RESEARCH

OPEN ACCESS

Effects and costs of implementing predictive risk stratification in primary care: a randomised stepped wedge trial

Helen Snooks,[1] Kerry Bailey-Jones,[2] Deborah Burge-Jones,[2] Jeremy Dale,[3] Jan Davies,[4] Bridie Angela Evans,[1] Angela Farr,[5] Deborah Fitzsimmons,[5] Martin Heaven,[1] Helen Howson,[6] Hayley Hutchings,[1] Gareth John,[7] Mark Kingston,[1] Leo Lewis,[8] Ceri Phillips,[5] Alison Porter,[1] Bernadette Sewell,[5] Daniel Warm,[9] Alan Watkins,[1] Shirley Whitman,[4] Victoria Williams,[1] Ian Russell[1]

► Additional material is published online only. To view please visit the journal online (http://dx.doi.org/10.1136/bmjqs-2018-007976)

For numbered affiliations see end of article.

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Check for updates

To cite: Snooks H, Bailey-Jones K, Burge-Jones D, *et al*. *BMJ Qual Saf* 2019;**28**:697–705.

ABSTRACT

Aim We evaluated the introduction of a predictive risk stratification model (PRISM) into primary care. Contemporaneously National Health Service (NHS) Wales introduced Quality and Outcomes Framework payments to general practices to focus care on those at highest risk of emergency admission to hospital. The aim of this study was to evaluate the costs and effects of introducing PRISM into primary care.

Methods Randomised stepped wedge trial with 32 general practices in one Welsh health board. The intervention comprised: PRISM software; practice-based training; clinical support through two 'general practitioner (GP) champions' and technical support. The primary outcome was emergency hospital admissions.

Results Across 230 099 participants, PRISM implementation increased use of health services: emergency hospital admission rates by 1 % when untransformed (while change in log-transformed rate Δ_L=0.011, 95% CI 0.010 to 0.013); emergency department (ED) attendance rates by untransformed 3 % (while Δ_L=0.030, 95% CI 0.028 to 0.032); outpatient visit rates by untransformed 5 % (while Δ_L=0.055, 95% CI 0.051 to 0.058); the proportion of days with recorded GP activity by untransformed 1 % (while Δ_L=0.011, 95% CI 0.007 to 0.014) and time in hospital by untransformed 3 % (while Δ_L=0.029, 95% CI 0.026 to 0.031). Thus NHS costs per participant increased by £76 (95% CI £46 to £106).

Conclusions Introduction of PRISM resulted in a statistically significant increase in emergency hospital admissions and use of other NHS services without evidence of benefits to patients or the NHS.

INTRODUCTION

The ageing population with rising prevalence of chronic conditions makes unprecedented demands on healthcare services.[1 2] In 2012–2013, there were 5.3 million emergency admissions to hospitals in England costing approximately £12.5 billion.[3] Around half of these admissions arise from 5% of the population—typically older people with comorbidities.[4] Patients with chronic conditions are more likely to experience emergency hospital admissions for potentially avoidable causes.[5] An emergency admission to hospital is disruptive and unsettling, exposing patients to clinical and psychological risks and increasing their dependency.[6]

An estimated one in five emergency admissions is avoidable,[7] especially when they arise from conditions amenable to community prevention or care.[8] Across Europe, policies have recommended that health providers use predictive risk stratification modelling to identify patients at high risk of emergency admission to hospital for proactive management.[9–12] In estimating individual risk scores, models typically include predictors relating to past use of healthcare, diagnoses and medications. The targeting of services at people at the highest levels of risk has been prominent in UK government policy over the past decade, notably within integrated care initiatives.[13 14] The National Health Service (NHS) England enhanced service, "Avoiding unplanned admissions: proactive case finding and patient review for vulnerable people", committed £480 million over 2014–2017[15] for general practices to create registers of patients at high risk of unplanned admissions for proactive case management. Over 95% of practices participated, most using predictive risk tools to identify patients for case

Validation of PRISM (n=51,600): c=0.749.

The model generally under-predicted risk at higher risk levels and over-predicted risk at the lowest risk level.

Introduction of the PRISM model into primary care resulted in **more** emergency hospital admissions and use of other NHS services without evidence of benefits to patients or the NHS.

Snooks H, et al.
BMJ Qual Saf 2019;28:697–705.

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Summary: Translation

- The translation of new systems/technologies to clinical practice is a complex process involving various steps
- Many clinical prediction models are published each year, but few are being used in clinical practice
- Even fewer models have been tested for the impact that they had on clinical decision making
- And when that happened, the results were not always positive

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Discussion

- Several models that had reasonable (or even good) predictive performance in validation sets, failed to improve health outcomes in clinical studies.
- What could be the explanation for this?

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What we have discussed in this lecture

1. Clinical prediction models
2. Clinical decision support
3. Translation: from research to clinical practice

Some recent papers from our group

Tsvetanova A, Sperrin M, Peek N, et al. Missing data was handled inconsistently in UK prediction models: a review of methods used. J Clin Epidemiol. 2021 Sep;140:149-58.

Lin L, Sperrin M, Jenkins DA, et al. A scoping review of causal methods enabling predictions under hypothetical interventions. Diagn Progn Res. 2021 Feb;5(1):3.

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Sisk R, Lin L, Sperrin M, et al. Informative presence and observation in routine health data: A review of methodology for clinical risk prediction. J Am Med Inform Assoc. 2021;28(1):155-66.

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Bull LM, Lunt M, Martin GP, et al. Harnessing repeated measurements of predictor variables for clinical risk prediction: a review of existing methods. Diagn Progn Res. 2020 Jul;4:9.

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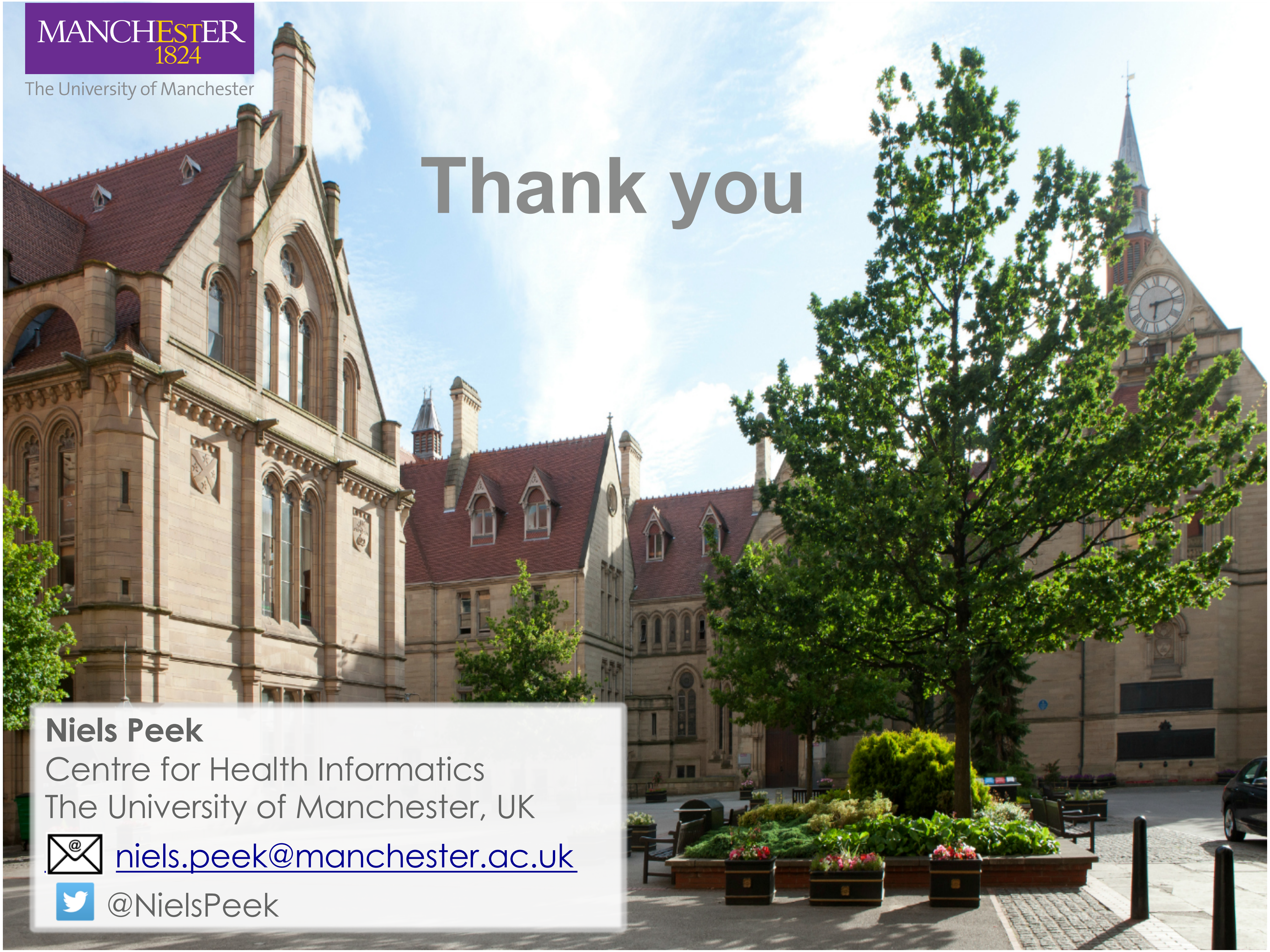

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Thank you

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