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# Artificial intelligence and datamining with biological data.

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ISLCCC 22  
Utrecht  
July 2022



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# Overview

- Case studies: Biological data science for late effects research
  - Original model
  - Validation
  - Application(s)
  - The future
- Common themes
- Techniques
- External validation
- Implications



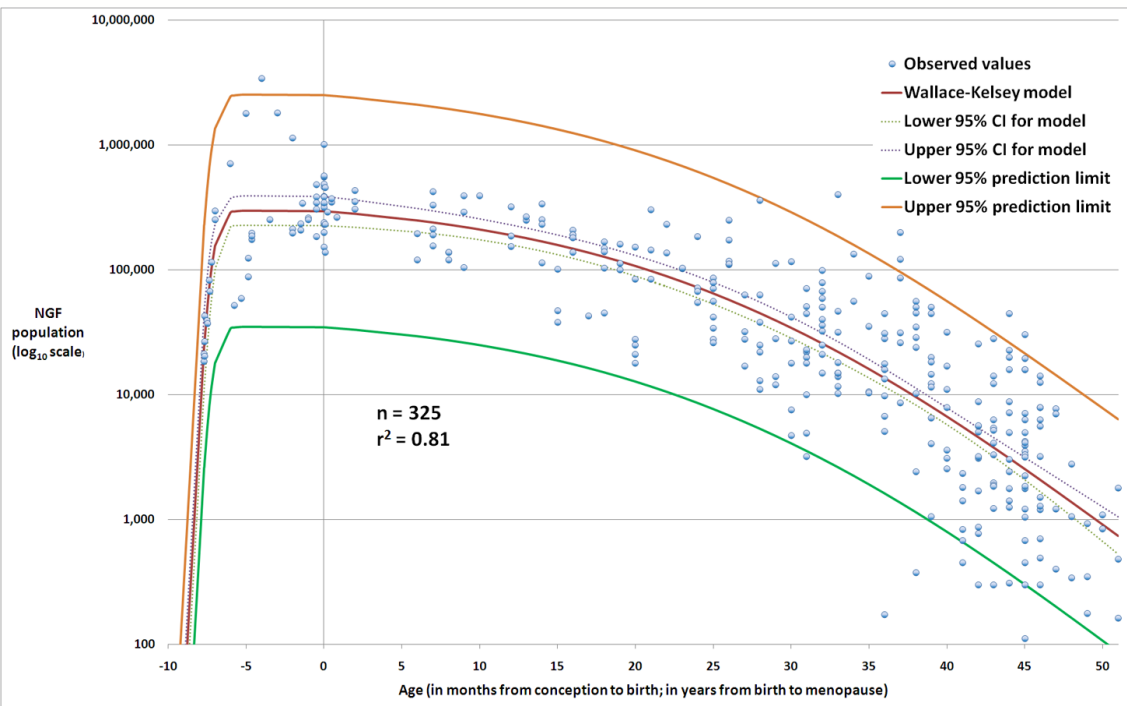
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# Methodology

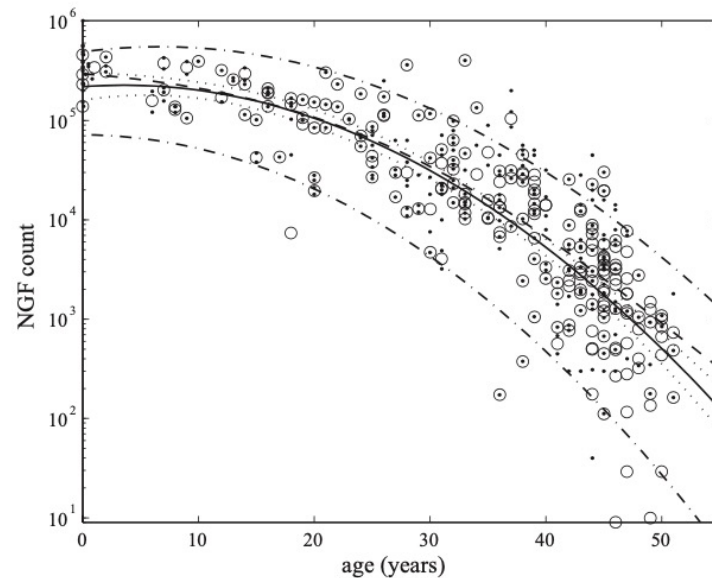
- Data aggregation
  - Systematic search for data sources from the literature
  - Tables, charts, descriptive statistics
  - Our own data – if available
- Data selection to create data set with minimal bias
  - Exclusion & inclusion criteria (e.g. exclude infertile)
- Homogeneous data set that approximates the healthy population for a wide range of ages
- Identify model with good fit to the data and low generalisation error
  - Accurate when used to predict unseen examples



## Number of potential eggs (NGFs) in the human ovary



## Predictions compared to later observations from a population-based cohort

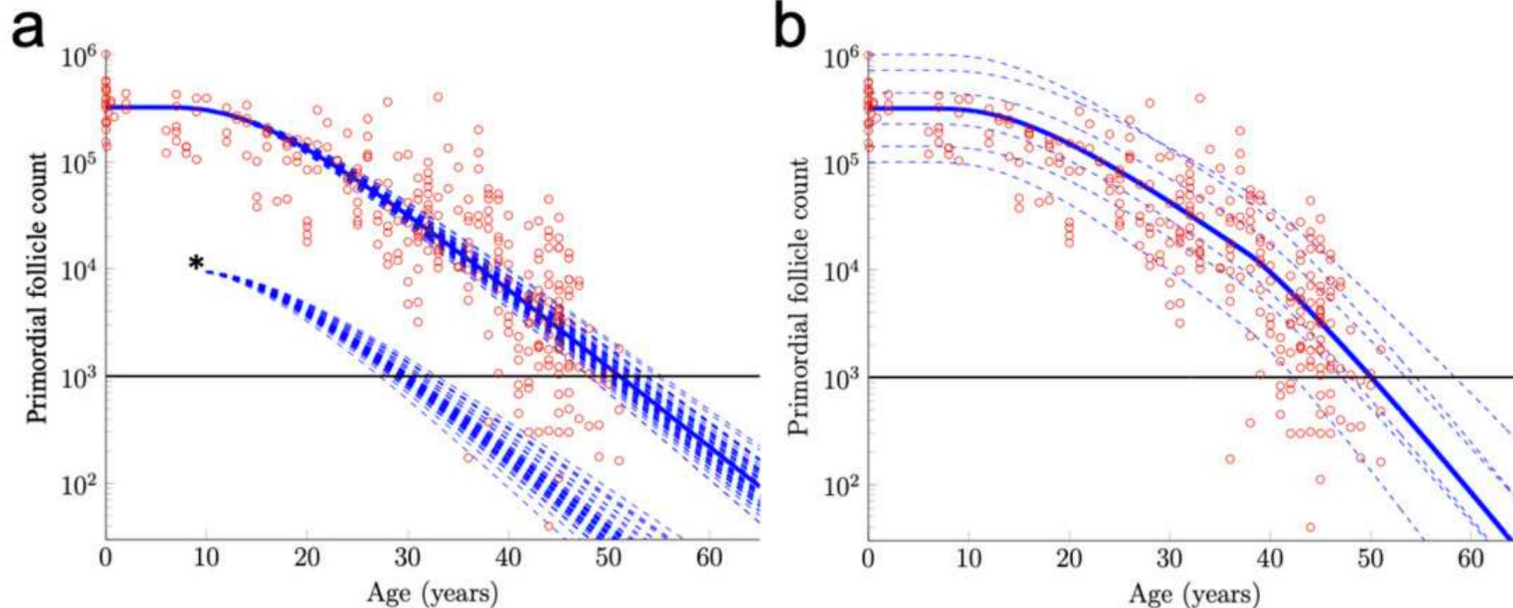


**Figure 1.** NGF counts (circles) from the 2015 data and (dots) from the 2010 data. The quadratic regression (solid line) fitted to the 2015 data with 95% confidence intervals (dotted lines) and 90% prediction intervals (dash-dotted lines). The Wallace-Kelsey model as fitted to the 2010 data is also depicted (dashed line).



# Random walk approach

Number of potential eggs (NGFs) in the human ovary





# Random walk approach

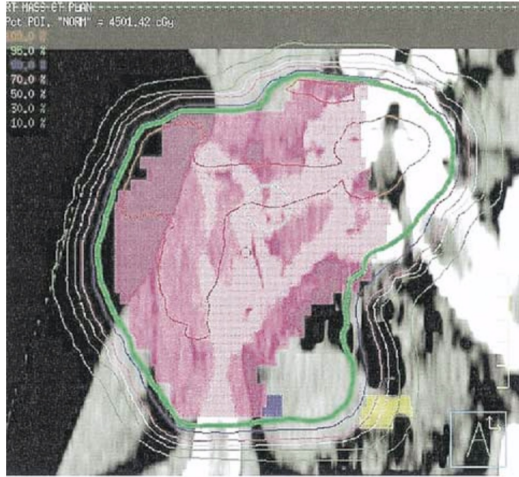
- Same data
- Good agreement with Wallace-Kelsey
  - In particular, accurate prediction of ages at menopause
- More modern technique (arguably)
  - Machine learning/AI method to remember or forget elements to optimise results
  - Stochastic gradient descent
- Can be used to test two important assumptions made by Wallace-Kelsey
  - High/low population at birth means late/early menopause
  - Radio- and/or chemotherapy moves a patient to an older age in terms of fertility, and decline is at the rate for the older healthy woman



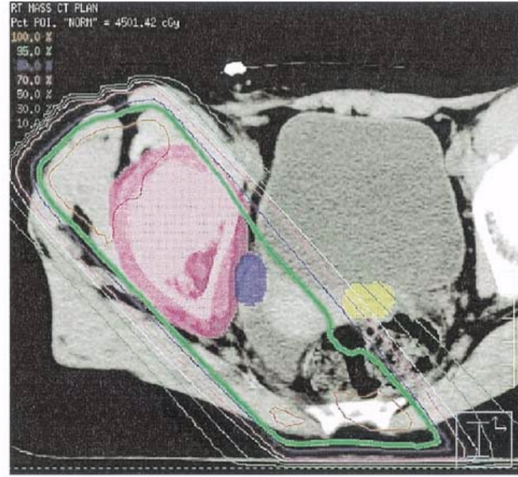
# Fertility after Radiotherapy

I. J. Radiation Oncology • Biology • Physics

Volume 62, Number 3, 2005



(a)



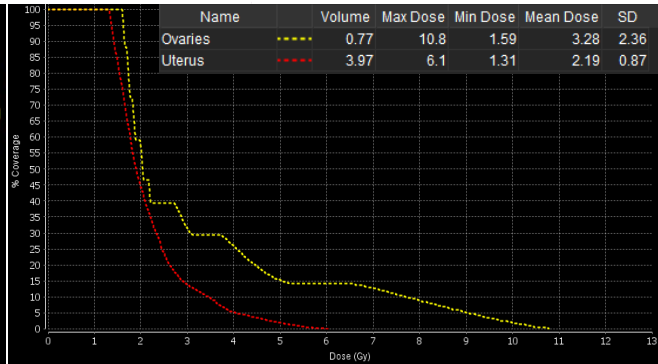
(b)

- Estimate LD<sub>50</sub> for the human oocyte
- Use to plan conformal RXT to optimise dose to the least-affected ovary
- Calculate window of opportunity for fertility
- Calculate the age-related effective sterilising dose
- Use to inform fertility preservation decision making

- Minimise the long-term effects of radiotherapy on healthy tissue
- Whilst maintaining cure rates



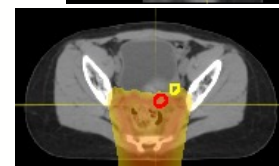
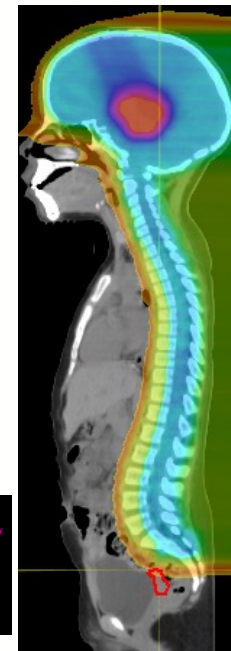
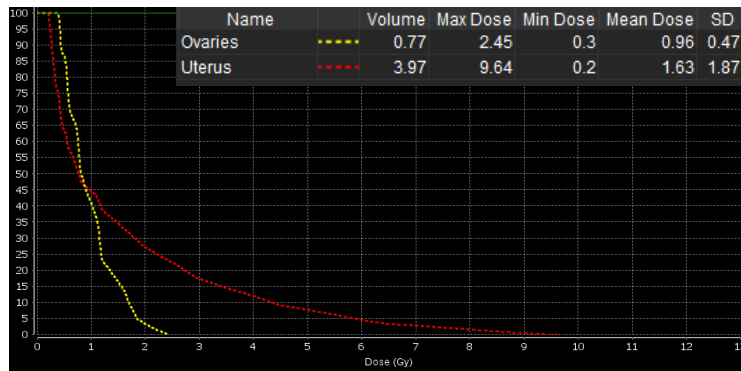
# Fertility after Radiotherapy



Photon  
Plan



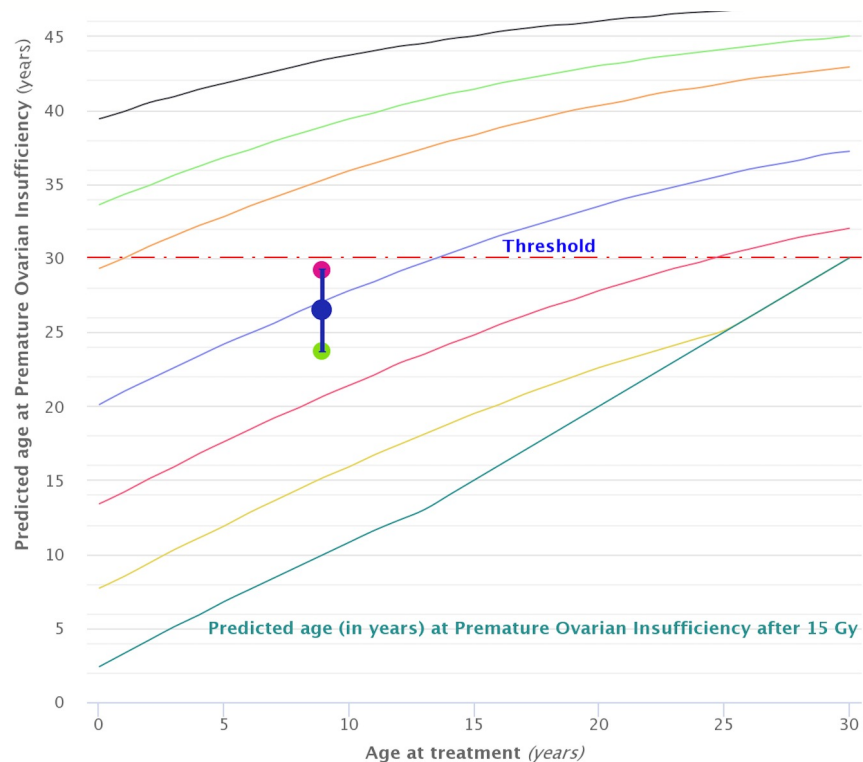
Proton  
Plan



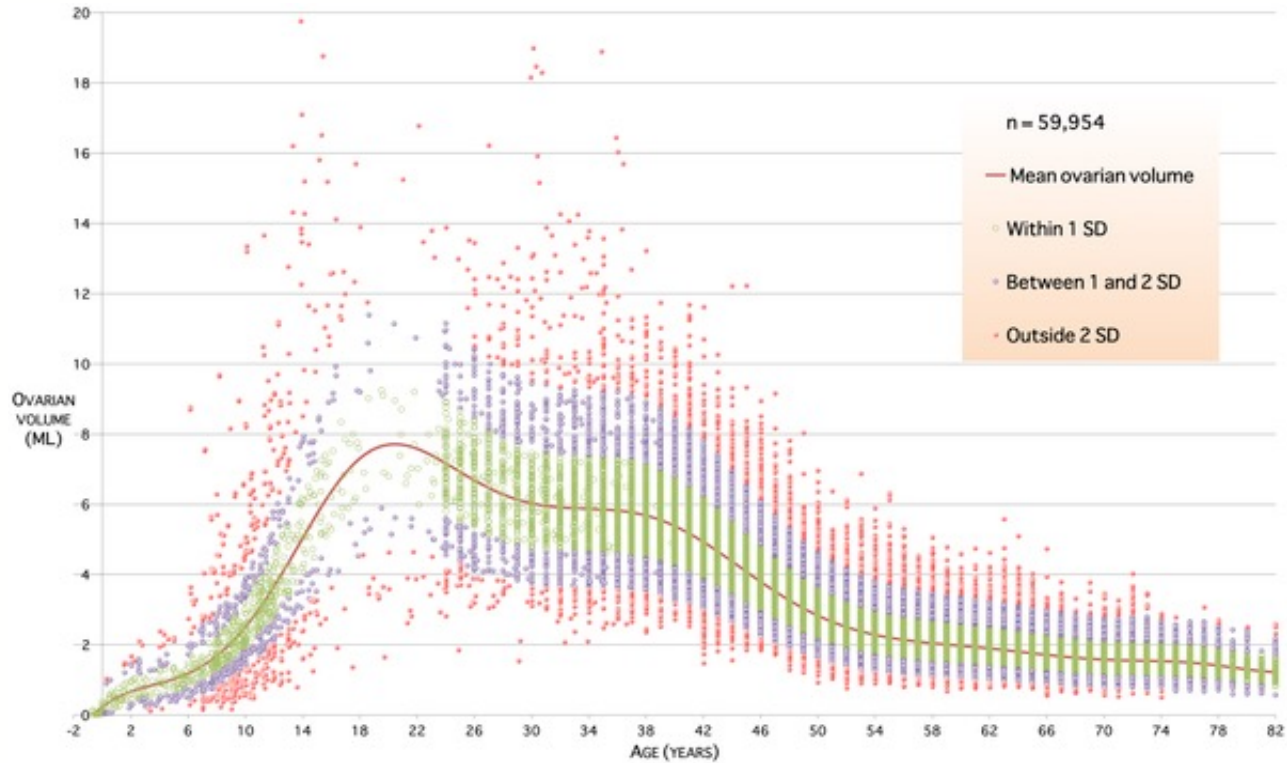


- 8.9 year old patient (say)
- CSI plan for Ewing sarcoma treatment with calculated min, max and mean dose to the least affected ovary
- Revised radiosensitivity modelling using externally validated model of ovarian reserve and best current estimate of LD<sub>50</sub>
- Estimate range of ages at premature ovarian insufficiency
- Useful for treatment planning
- Also an illustrative tool informing fertility preservation discussions

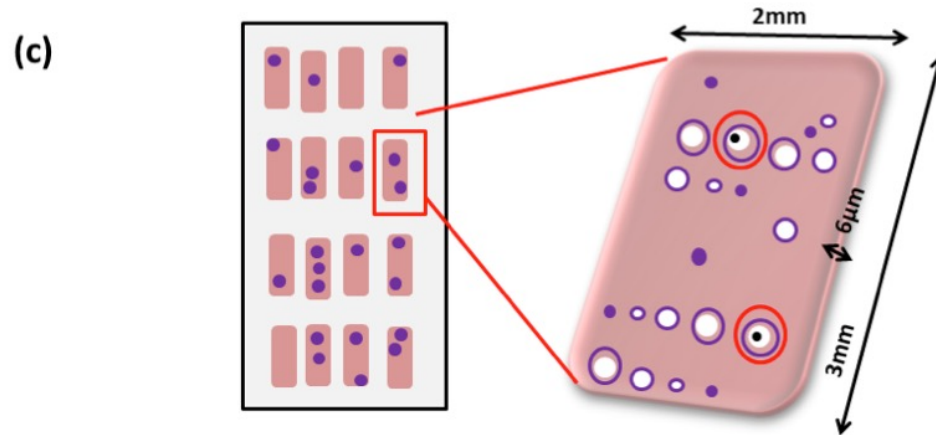
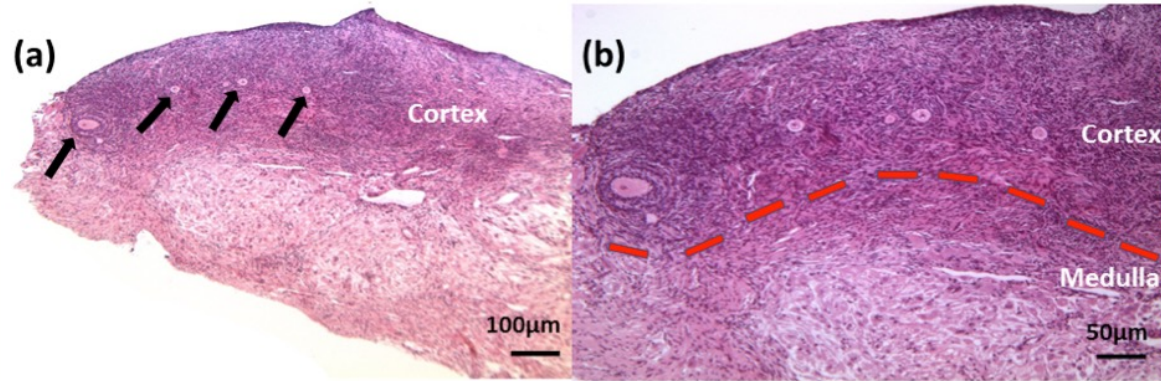
## Fertility after Radiotherapy



# Observational data model – ovarian volume



# Follicle density

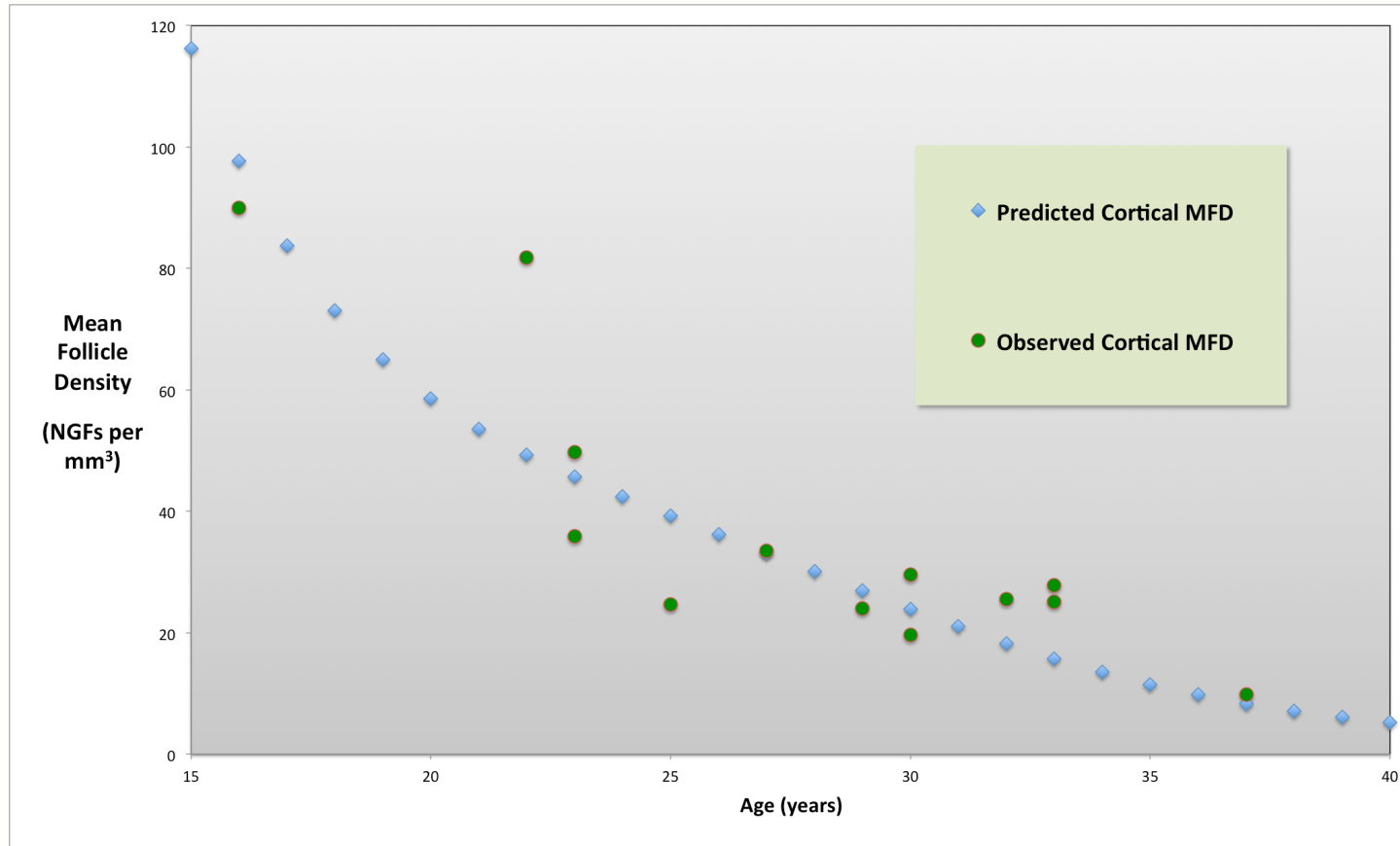




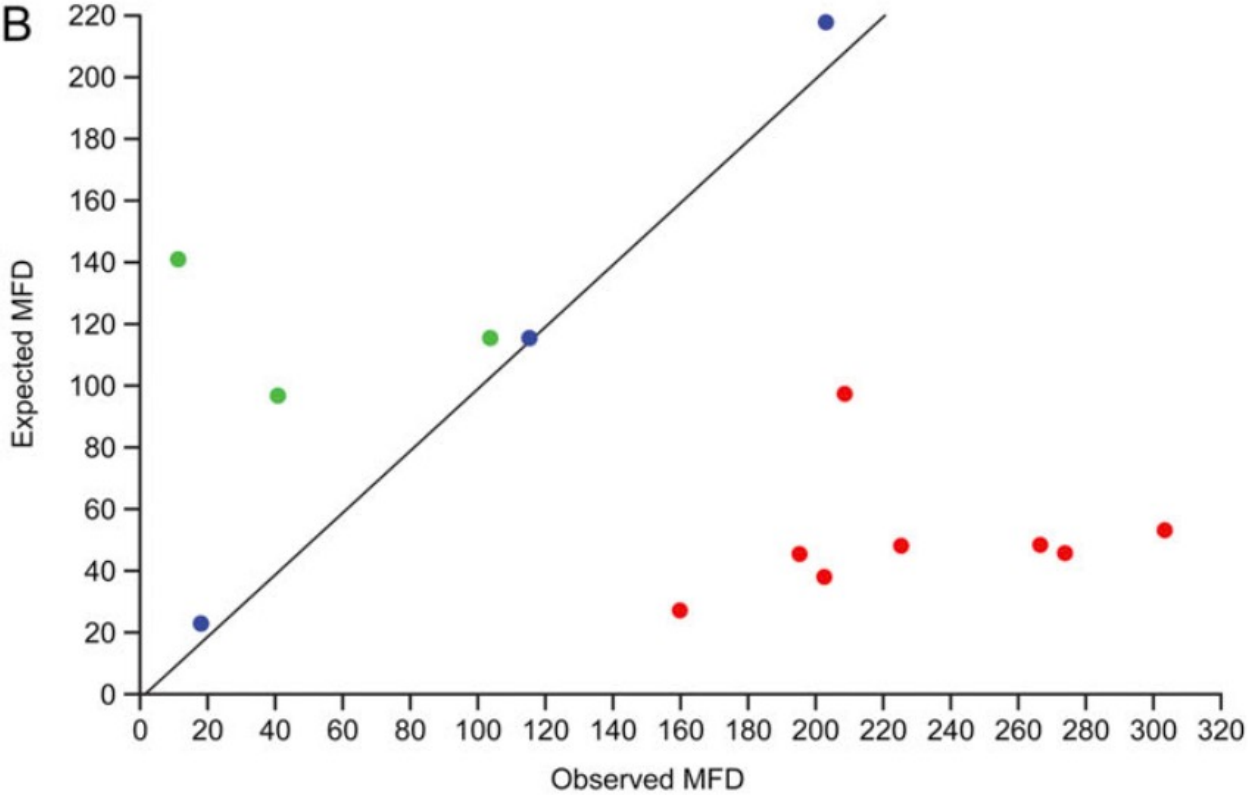
# A model to predict Mean Follicle Density for healthy females aged 15 – 37 years

- Assumption: a large ovary contains more eggs than a small one
- NGFs: use the Wallace-Kelsey model to estimate NGF population, giving  $\text{NGF}(\text{age})$
- Volume: use our model to estimate the ovarian volume, giving  $\text{Volume}(\text{age})$
- Predicted  $\text{MFD}(\text{age})$  is then  $\text{NGF}(\text{age})$  divided by  $\text{Volume}(\text{age})$
- (We have to adjust for the proportion of a typical ovary that consists of cortical tissue)
- Simple arithmetic – no AI, no advanced statistics
- Sophisticated and modern techniques are not always required

# External Validation of NGF and OV Models

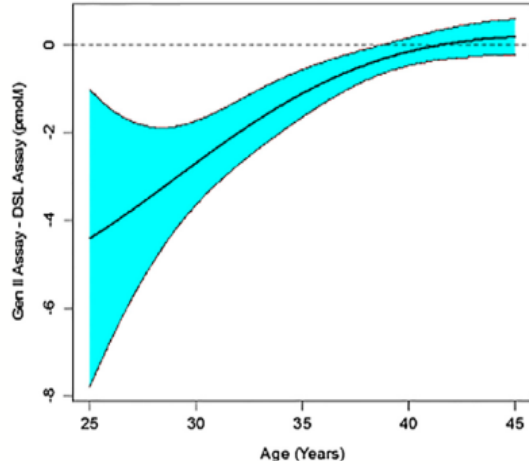


# Using the models to assess NGF density after ABVD

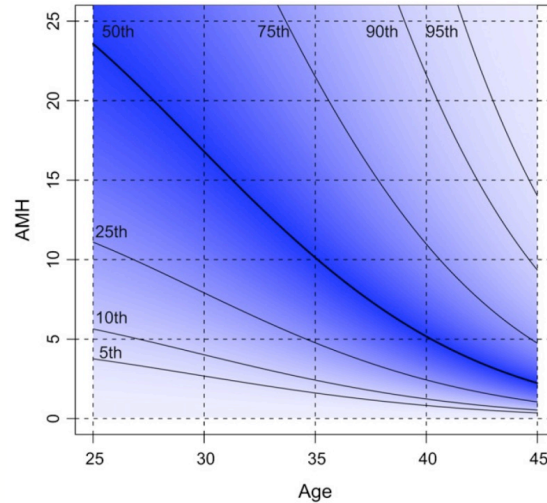




# Observational data approaches have been critical to our understanding of AMH and its utility



Derived N = 5,492  
Validated N = 5,492  
Compared N = 9,601



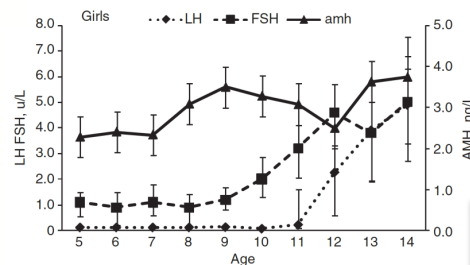
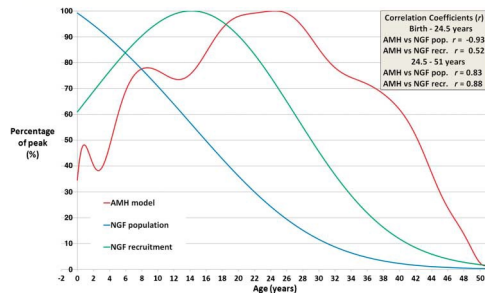
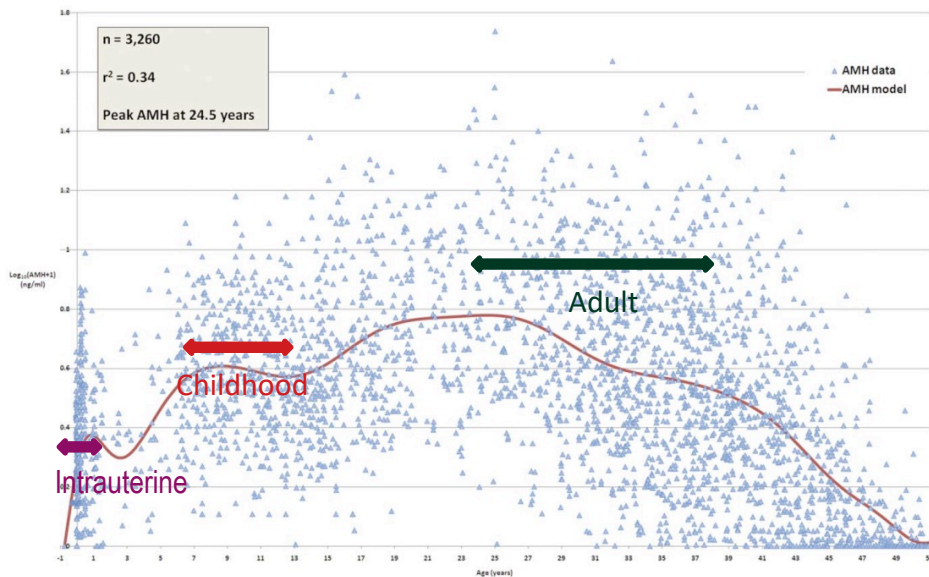
Derived = 9,601  
Validated in N = 15,834

- AMH is a product preantral and small antral follicles in women
- As such, AMH is only present in the ovary until menopause
- **Can it be used as a biomarker for remaining ovarian reserve?**
- First studies are promising, but are based on infertile subjects





# Observational data approaches have been critical to our understanding of AMH and its utility

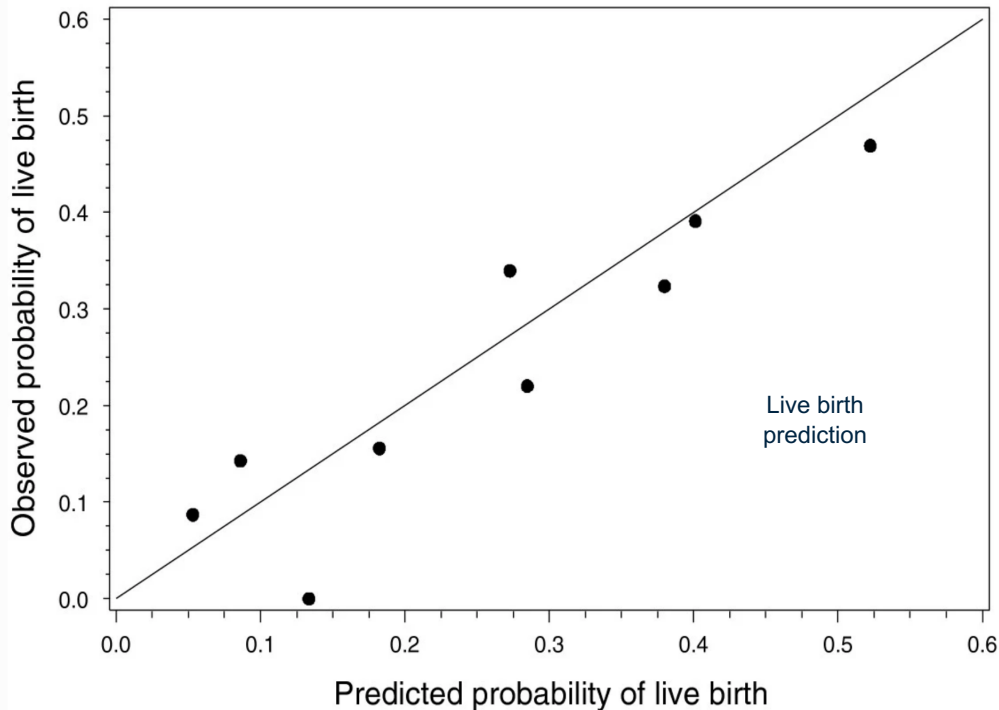


- AMH model from conception to menopause
- Validated for adult ages
- Validated for childhood/pubertal ages using 10-year longitudinal data

- AMH now accepted as biomarker



# Observational data approaches have been critical to our understanding of AMH and its utility

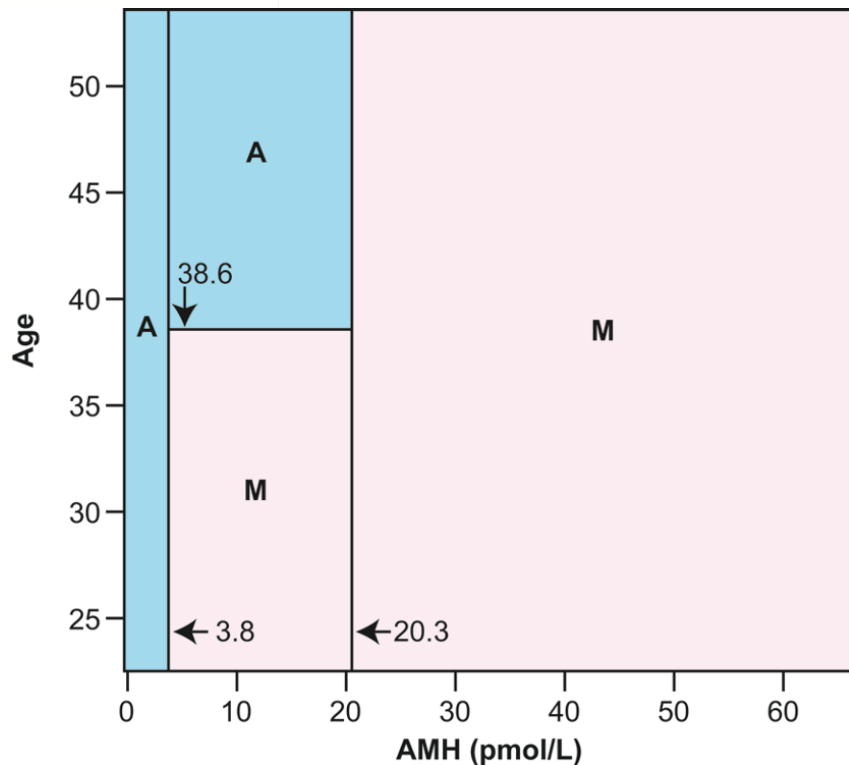


- “Our findings provide genetic support for the well-established use of AMH as a marker of ovarian reserve”
- AMH now routinely used as adjunct to the 2003 criteria for PCOS diagnosis
- Predicted live births based on AMH match observations

- AMH now used effectively as a biomarker
- Providing further validation of the underlying models



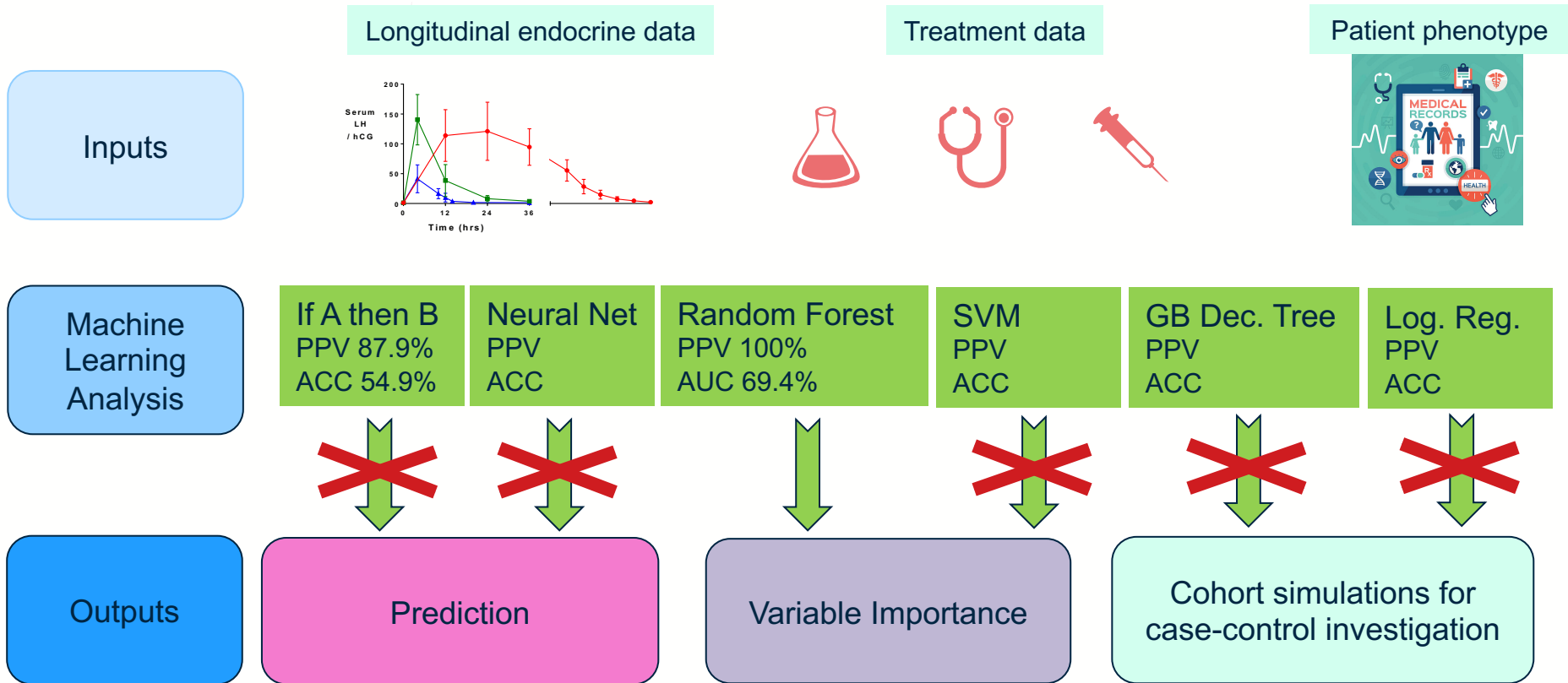
# Using AMH to inform fertility preservation for survivors of cancer



- Pre-treatment AMH predicts for loss of ovarian function after chemotherapy for early breast cancer
- 6-month post-treatment AMH has high PPV for impaired fertility
- Pre- and post-chemo AMH combined with BMI, age, parity and endocrine factors has high diagnostic utility

- We can optimise and personalise post-chemo endocrine therapy

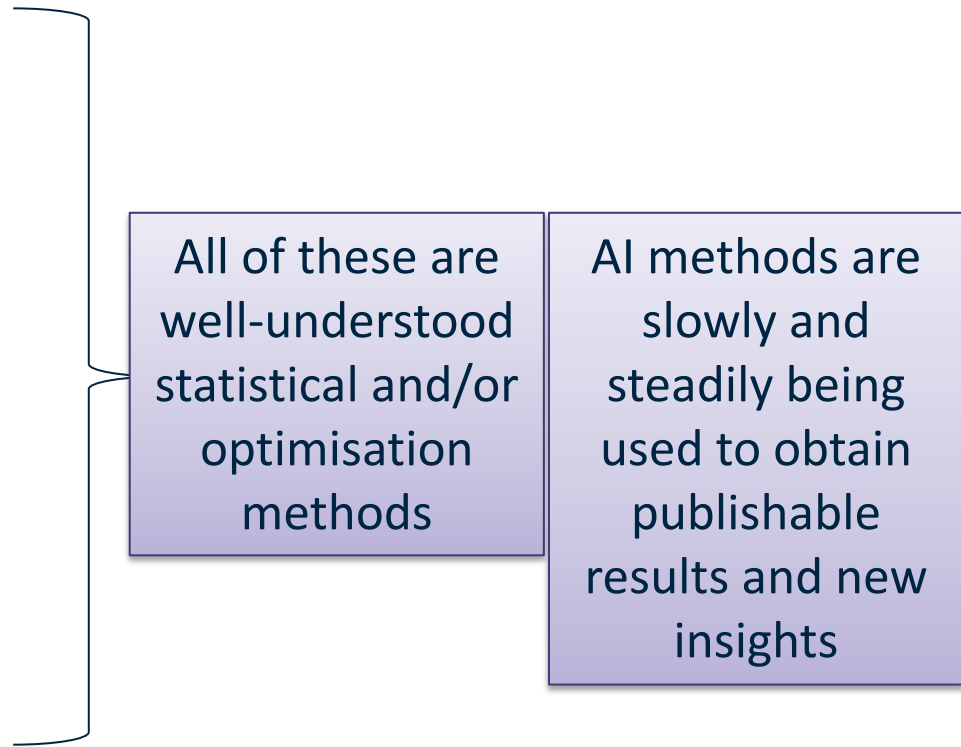
# AI as a strategy to improve endocrine therapy after breast cancer





# Where is the modern AI?

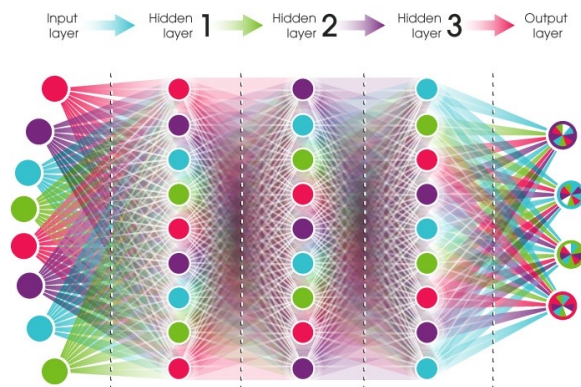
- Cohort studies
  - Regression models
  - Multivariable logistic regression
  - Dose-response models
- Observational data studies
  - Life tables using Kaplan-Meier
  - PK style modelling using ODEs
  - Cox proportional hazards
  - Normative age-related models
- Meta analyses
  - Hierarchical summary ROC curves
  - Fixed & random effects meta-regression





# Due process of AI studies still required

## Deep neural network



- Publish in accordance with existing reporting standards

## Clinical validation in real-world medicine



- Publish, RCTs showing benefit, Regulatory approval

## Implementation in healthcare



- Cost of implementation
- how many workflows will be affected?
- Does the model increase the efficiency of existing workflows?
- Is the model being deployed within an existing digital workflow?

Slide taken from Scot Nelson, 2020



# Conclusions

- Careful identification and analysis of biomedical data can lead to models
  - All of these models are wrong
  - Some of them are useful
- The key measure of utility is **external validation**
  - Predictions match observations for new and/or unseen data
- Many of the techniques used are old and well understood
- AI and machine learning techniques are becoming more prevalent, with notable improvements on existing knowledge
- But the specific method used is less important than validation



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# Colleagues

- Edinburgh
  - Hamish Wallace, Richard Anderson, Evelyn Telfer, ...
- Copenhagen
  - Stine Gry Kristensen, Linn Mamsen, Claus Yding Andersen, ...
- Imperial College
  - Ali Abbara, Waljit Dhillon, ...
- Glasgow
  - Scott Nelson, Stamatina Iliodromiti
- St Andrews
  - Gerry Humphris, Frank Sullivan, ...





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Thank you

