

**56**<sup>th</sup> Annual Meeting & **42**<sup>nd</sup> Post Graduate Course

#### jESPeR Lecture

## Artificial intelligence in cardiac imaging

Andrew Taylor Professor of Cardiovascular Imaging - UCL Institute of Cardiovascular Science Director of Innovation - Great Ormond Street Hospital for Children





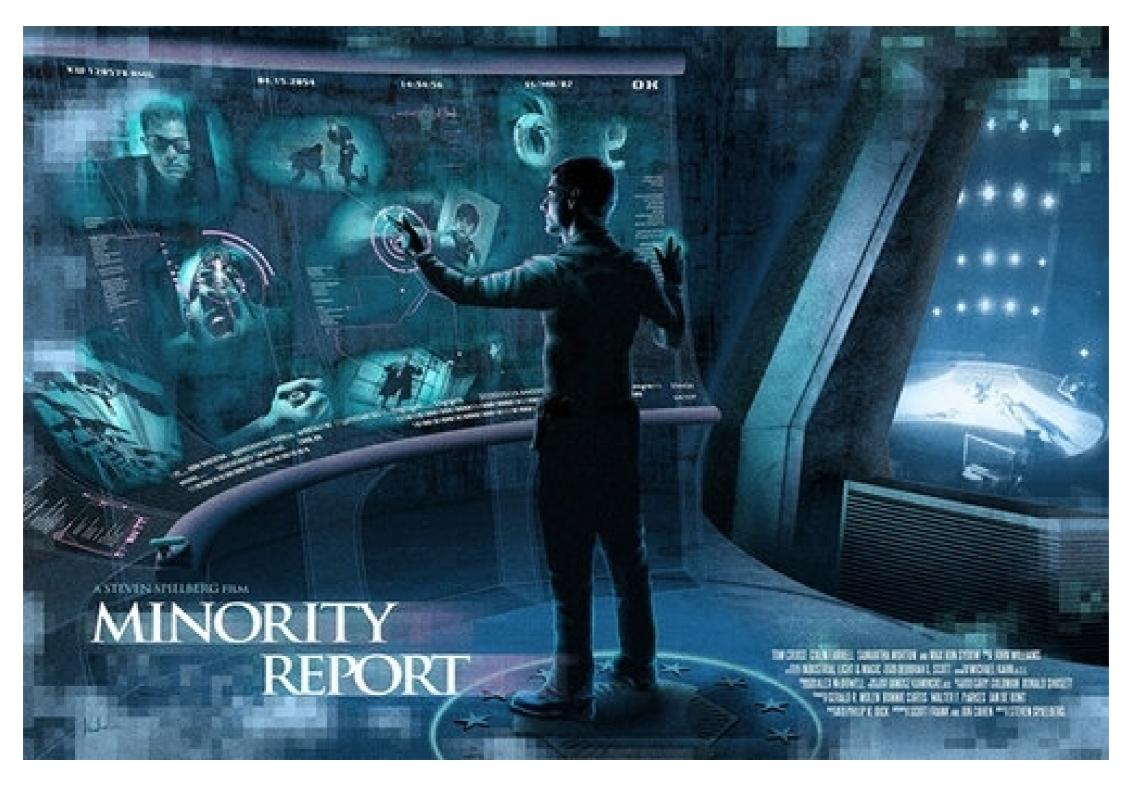
#### Disclosures

**Medtronic speaker** 

#### Hospital funding via Sensyne, ViroCell, Roche

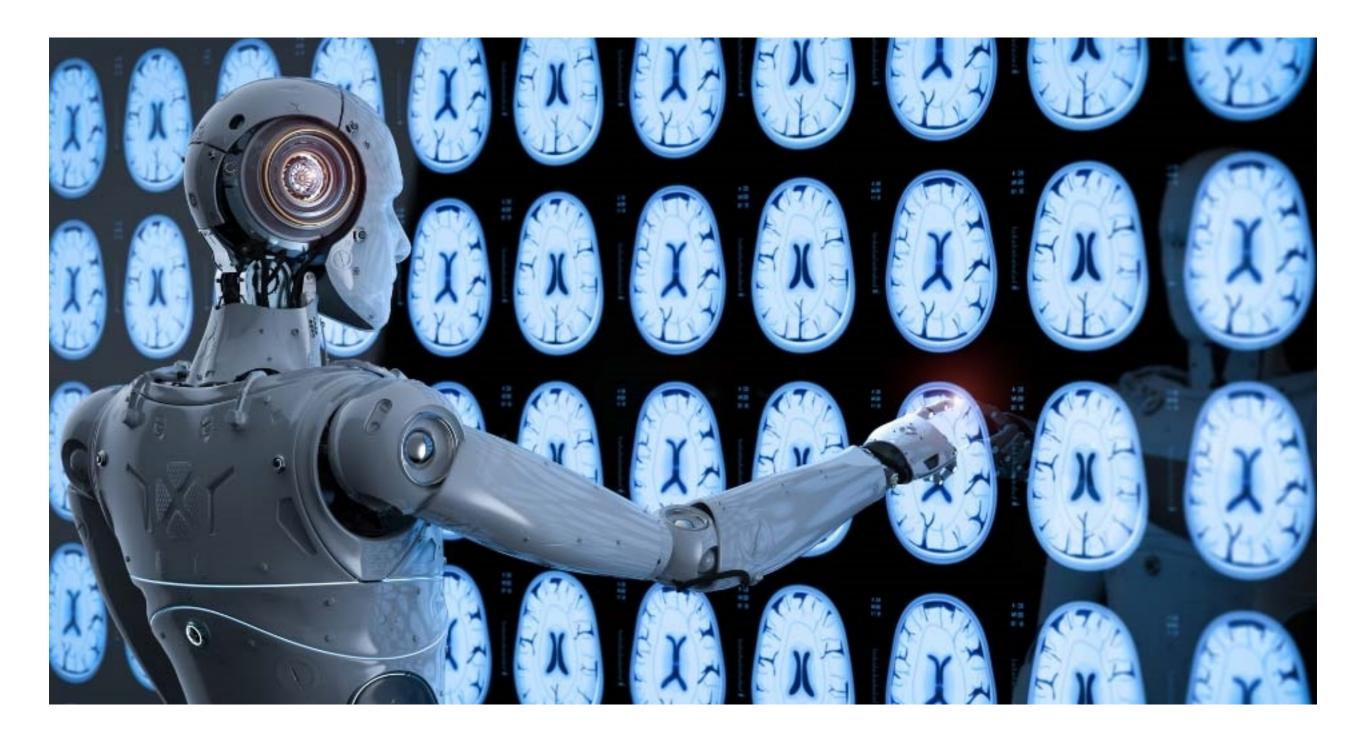
















### Artificial intelligence and machine learning

AI is the ability to sense, reason, engage & learn

Machine learning is the ability to learn

Though ML forms the basis of most AI systems and may look intelligent, it isn't!





#### **Al definitions**

Artificial intelligence is a computerised system that exhibits behaviour that is commonly thought of as requiring intelligence

or

Artificial intelligence is the science of making machines do things that would require intelligence if done by man





#### **Al definitions**

## The founding father of AI, Alan Turing, defines this discipline as:

"AI is the science and engineering of making intelligent machines, especially intelligent computer programs."





#### **Al concepts**



#### PROBLEM SOLVING

https://www2.deloitte.com/se/sv/pages/technology/articles/part1artificial-intelligence-defined.html





### What is Al good at

Narrow well defined problems:

- face recognition
- chess computers
- calculus, translation

General AI is the 'holy-grail'





#### Al beats the human!





#### AlphaGo

**Convolutional Neural Network** 

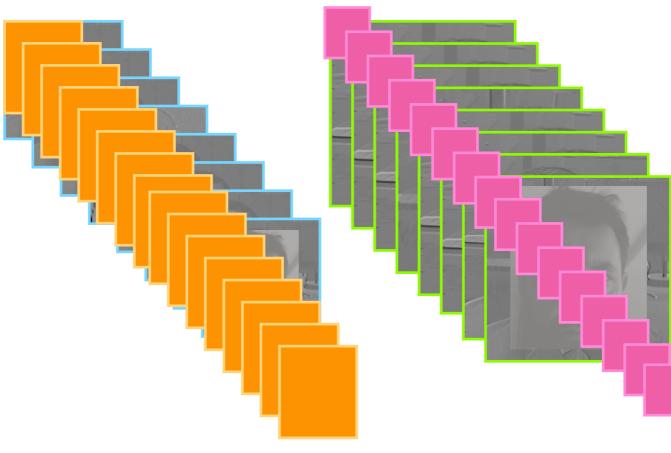






## Convolutional neural network







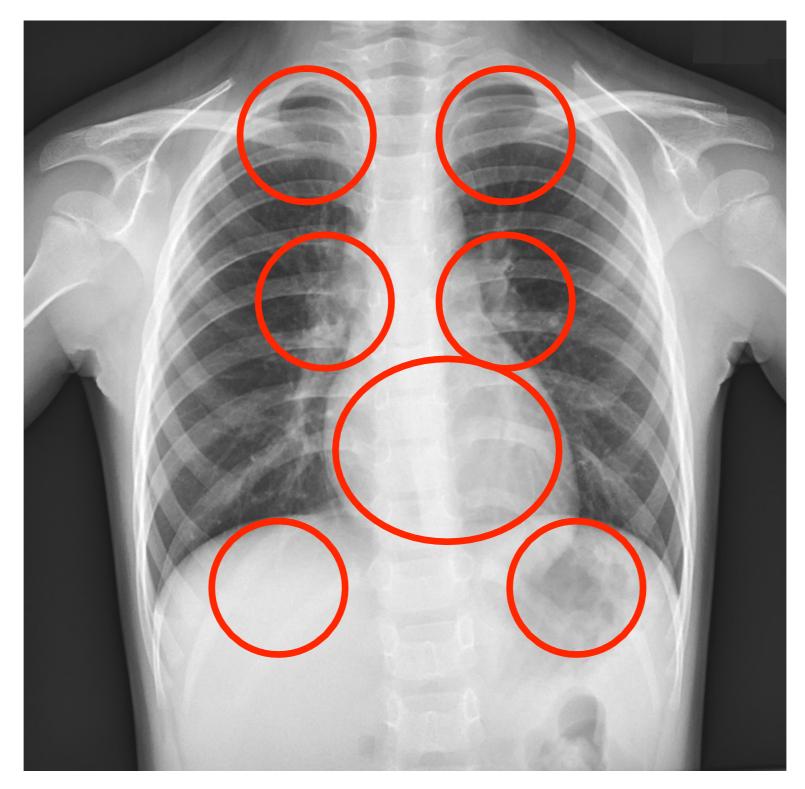


# The simple chest x-ray





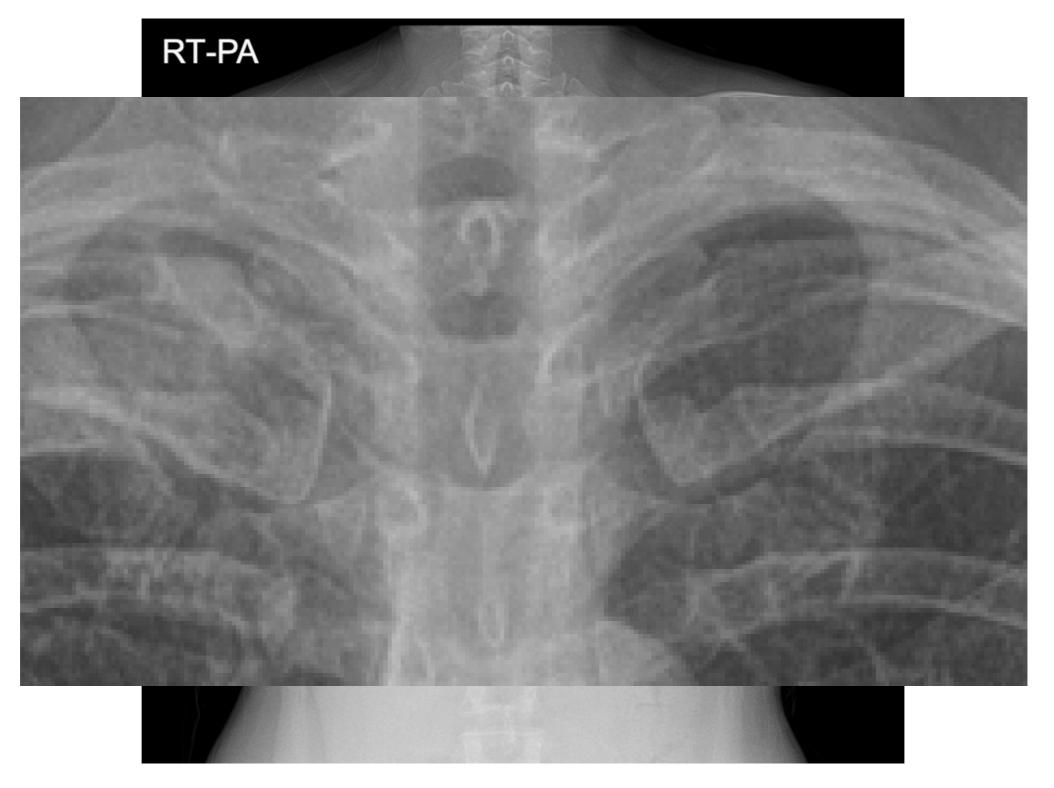
#### **Defining normal**







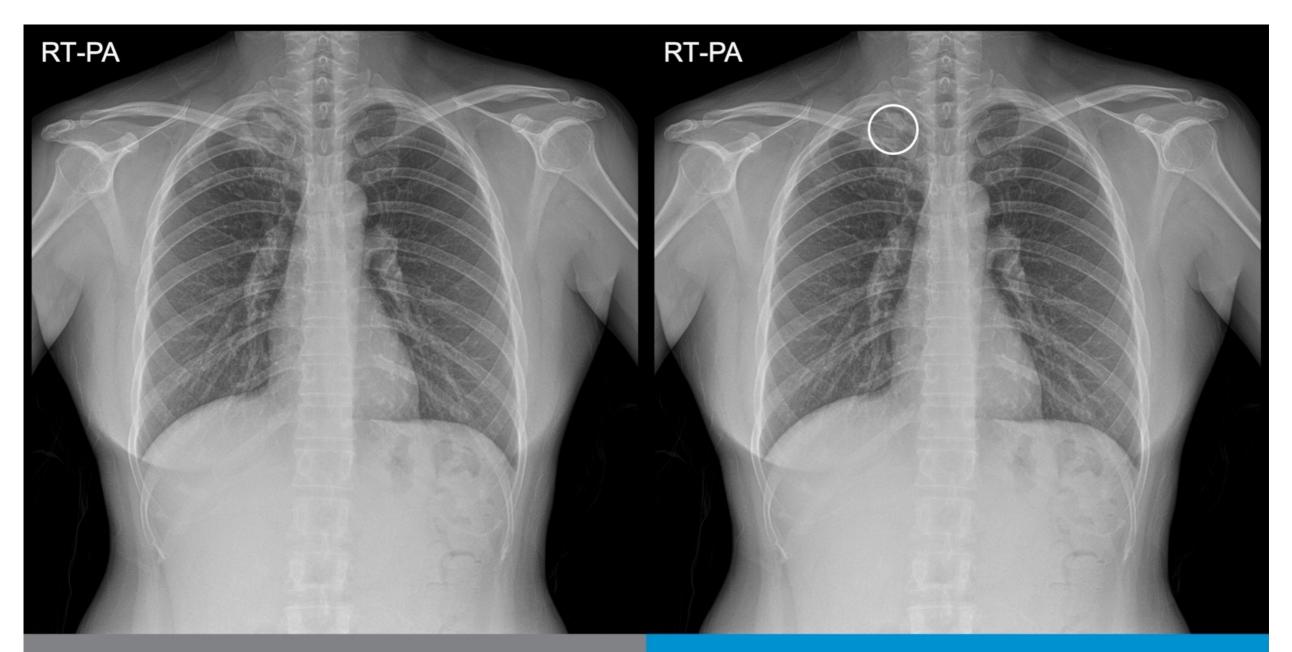
#### Single glance







#### Al as decision support



#### Without ALND

#### With ALND

Auto Lung Nodule Detection





#### Al and radiology

"This FDA clearance is a huge milestone for Samsung and is the result of our tireless work to design diagnostic solutions that empower providers to deliver patients the absolute best care possible"





#### Al for decision support

#### Sensitivity of this algorithm is about 80%

Important question is not whether is replaces me - my accuracy is 95% (97.5% if double reported - but does it improve my accuracy?



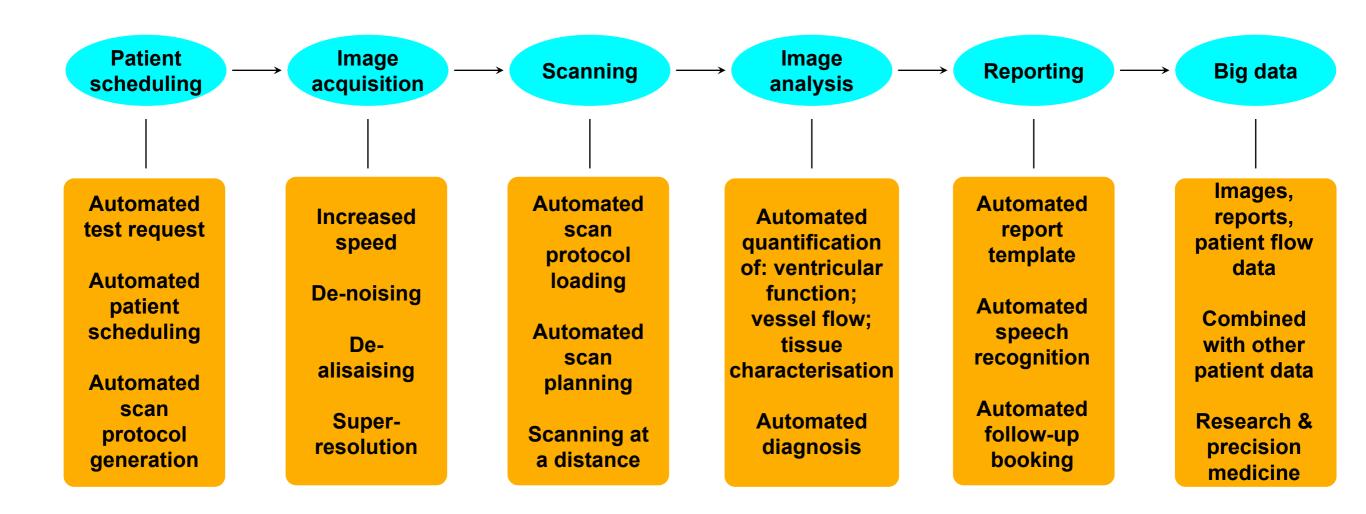


## Al shouldn't be scary





## My imaging pathway







## Better scheduling, reporting, scanning





#### **Ordering tests**

## At **least 80% of imaging** requests do not have the relevant clinical information

AI tools can extract clinical information from the clinical electronic patient record (EPR) to improve imaging modality selection and then drive protocolisation

An ML tool was able to analyse unstructured text for clinical indications for neurological MRI requests and appropriately protocolise the MR scan, **with an accuracy of 95%** 





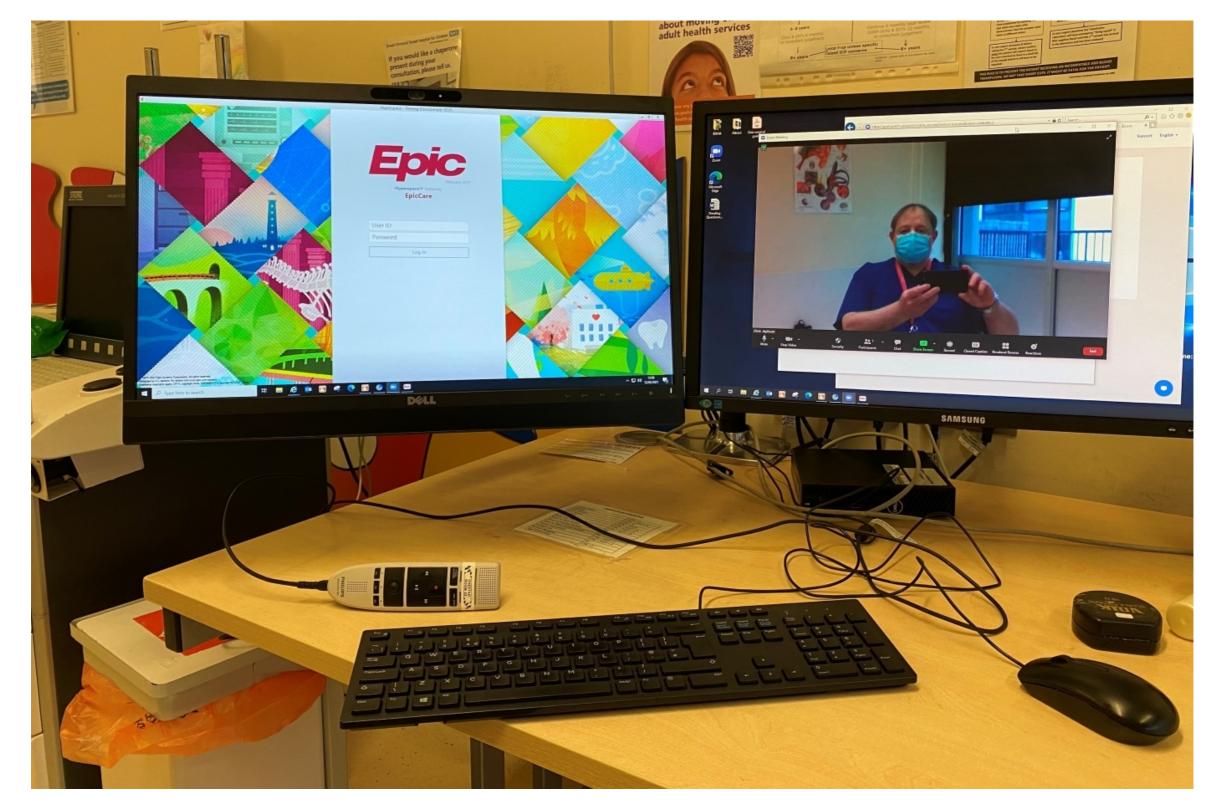
#### **Better processes**

Algorithms can also be used to support optimisation of scheduling to:

- define optimal times for appointment bookings
- predict which patients may not attend
- define optimal follow-up times
- automatically book follow-up imaging











## Faster image acquisition



### **Be fast - acquisition**

Walheim et al. Journal of Cardiovascular Magnetic Resonance https://doi.org/10.1186/s12968-019-0549-0 (2019) 21:42

Journal of Cardiovascular Magnetic Resonance

#### **TECHNICAL NOTES**

Multipoint 5D flow cardiovascular magnetic resonance - accelerated cardiac- and respiratory-motion resolved mapping of mean and turbulent velocities



**Open Access** 

Jonas Walheim<sup>\*</sup>, Hannes Dillinger and Sebastian Kozerke



## **Be fast - acquisition**

- Aim To develop a 5D Flow CMR framework which combines undersampled data acquisition, including multipoint velocity encoding with low-rank image reconstruction of cardiac- and respiratorymotion
- **Method** 9 subjects comparing 5D flow with 4D flow for the assessment of velocity maps and turbulent kinetic energy
- Results Net scan time of 5D Flow CMR was 4 min vs. 17.8 ± 3.9 min for 4D flow protocol. On average, peak velocities assessed with 5D Flow CMR were higher than for the 4D protocol (3.1 ± 4.4%)



### **Be fast - reconstruction**

ARTICLES https://doi.org/10.1038/s42256-020-0165-6



Check for updates

#### Deep variational network for rapid 4D flow MRI reconstruction

Valery Vishnevskiy<sup>1,2</sup><sup>2</sup>, Jonas Walheim<sup>1,2</sup> and Sebastian Kozerke<sup>1</sup>





#### **Be fast - reconstruction**

- The network is shown to reconstruct under-sampled 4D flow MRI data in under a minute on standard consumer hardware
- Remarkably, the network was trained on images from 11 reference scans while generalising well to retrospective and prospective undersampled data for various acceleration factors and anatomies

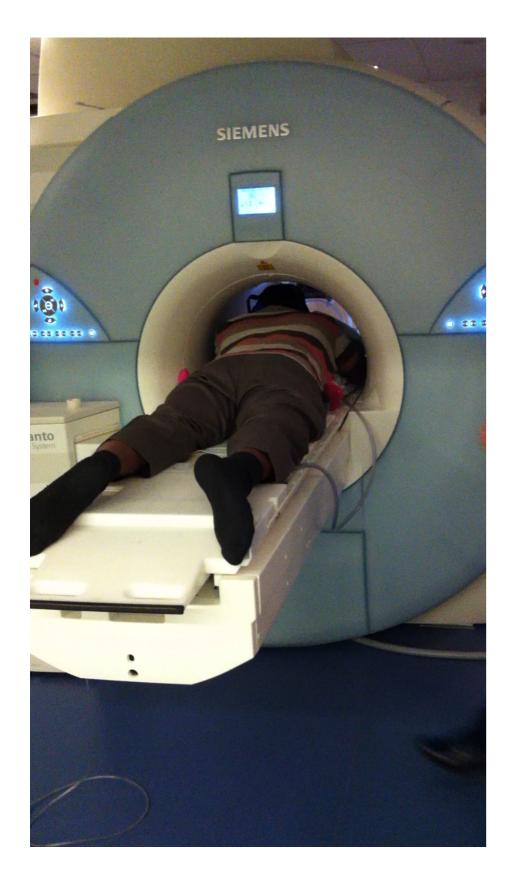
**Table 1 | Model complexities and typical reconstruction time for**4D flow reconstruction

Method	Reconstruction time	No. of parameters
CS-LLR	10 min 24 s	2
HamVN	89 s	62,742
FlowVN	21 s	63,583

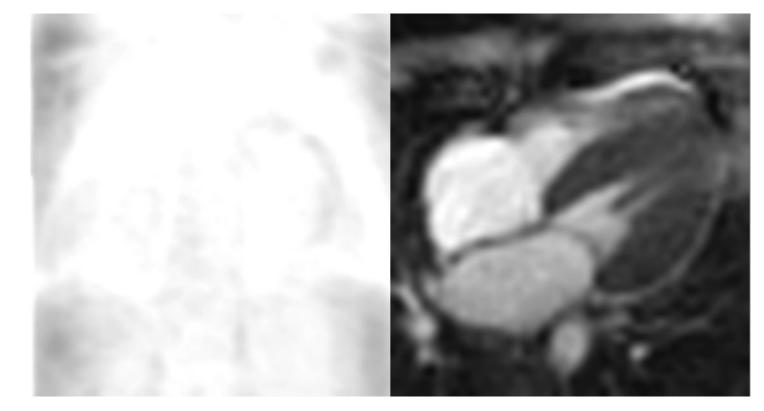
Typical reconstruction times are shown for four-point velocity encoded data compressed to five virtual coils and reconstructed on a  $113 \times 113 \times 25$  grid. CS-LLR was executed on a six-core Intel CPU; FlowVN and HamVN were implemented in Tensorflow and evaluated on a NVIDIA Titan RTX system.

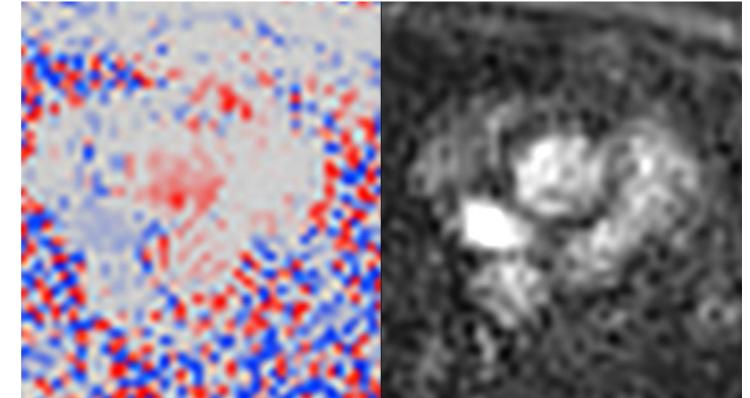






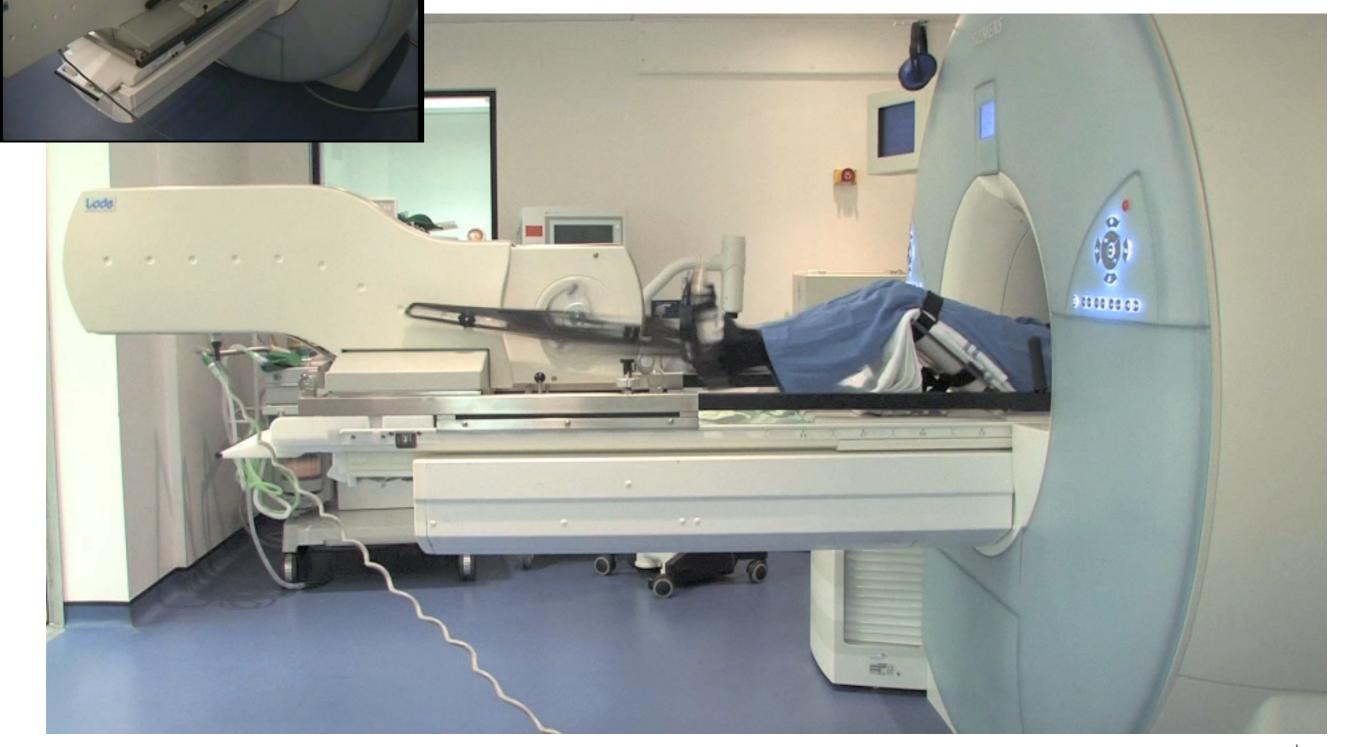
#### **Real-time imaging in PH**











Q,





# Faster image analysis

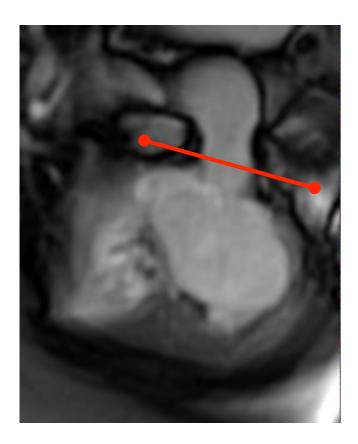


## Quantify size and shape

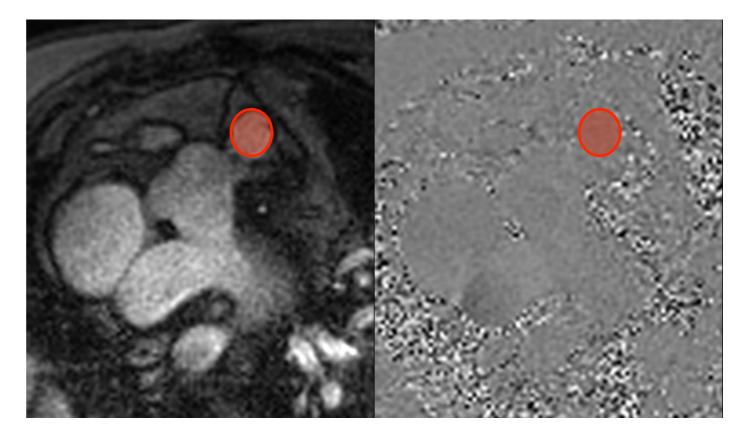


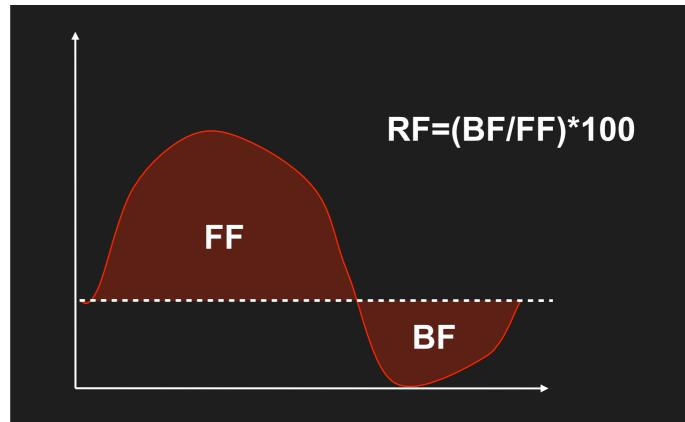
Schievano S, et al. Radiology 2007; 242:490-7





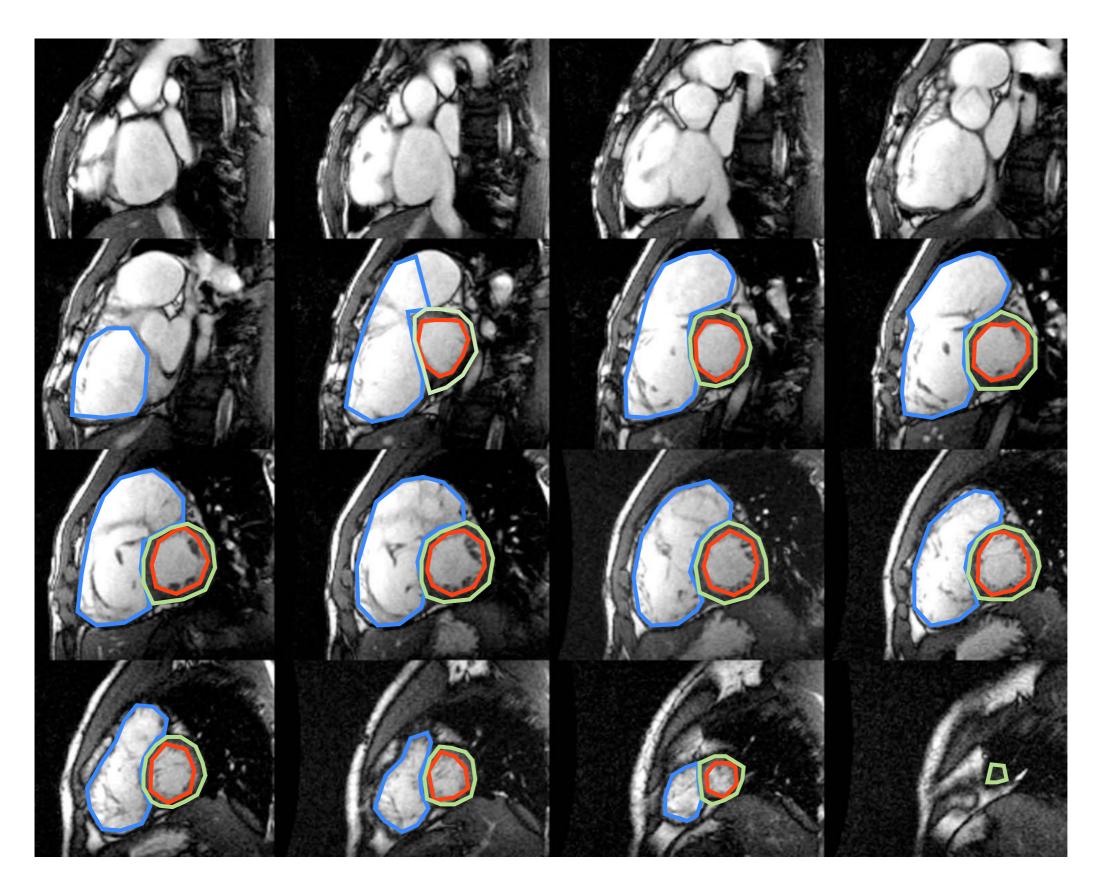
## **Quantify flow**



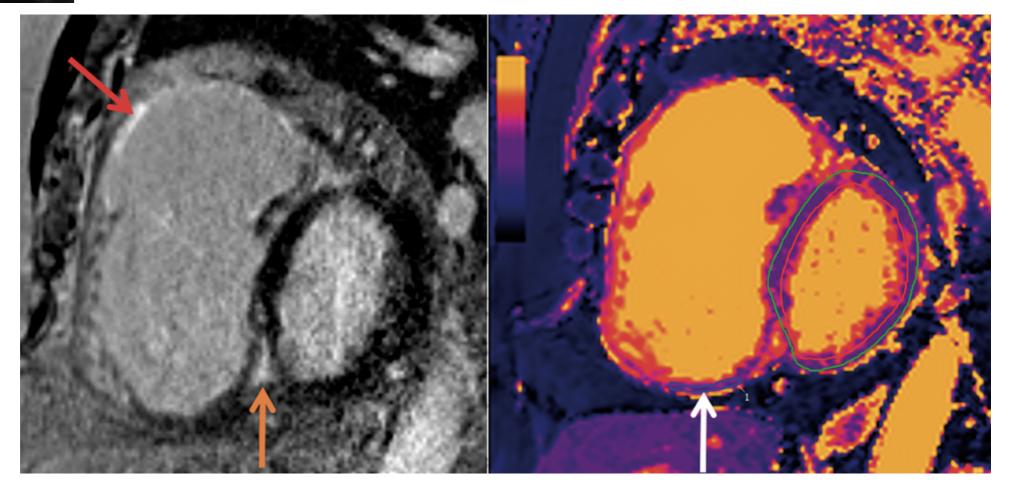




## **Quantify volumes**



### Quantify tissue characterisation



#### Hanneman et al. EHJ CVI 2018



#### Automated flow analysis

Bratt et al. Journal of Cardiovascular Magnetic Resonance https://doi.org/10.1186/s12968-018-0509-0 (2019) 21:1

Journal of Cardiovascular Magnetic Resonance

#### RESEARCH



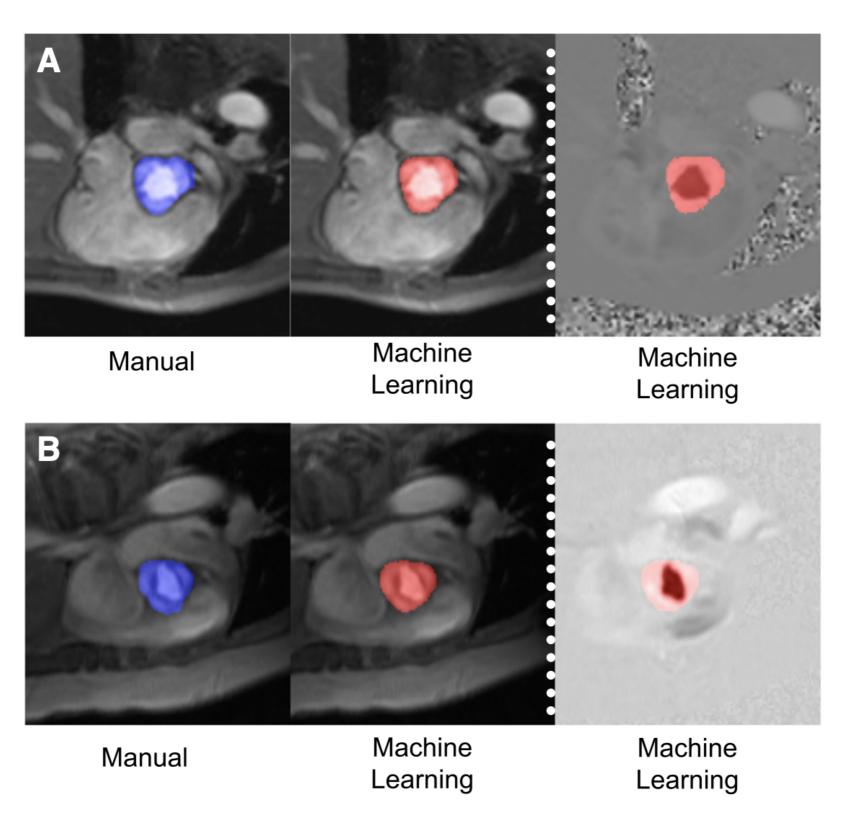
**Open Access** 

#### Machine learning derived segmentation of phase velocity encoded cardiovascular magnetic resonance for fully automated aortic flow quantification

Alex Bratt<sup>1</sup>, Jiwon Kim<sup>1,2</sup>, Meridith Pollie<sup>2</sup>, Ashley N. Beecy<sup>2</sup>, Nathan H. Tehrani<sup>2</sup>, Noel Codella<sup>3</sup>, Rocio Perez-Johnston<sup>4</sup>, Maria Chiara Palumbo<sup>2</sup>, Javid Alakbarli<sup>2</sup>, Wayne Colizza<sup>1</sup>, Ian R. Drexler<sup>1</sup>, Clerio F. Azevedo<sup>5</sup>, Raymond J. Kim<sup>5</sup>, Richard B. Devereux<sup>2</sup> and Jonathan W. Weinsaft<sup>1,2,4,6\*</sup>



#### Automated flow analysis





## Automated flow analysis

- Method A machine learning model was designed to track aortic valve borders based on neural network approaches. The model was trained on 150 patients who underwent clinical PC-CMR then compared to manual and commercially-available automated segmentation in a prospective validation cohort of 190 patients.
- Results Machine learning segmentation was uniformly successful, requiring no human intervention: Segmentation time was < 0.01 min/case (1.2 min for entire dataset); manual segmentation required 3.96 ± 0.36 min/case (12.5 h for entire dataset).



#### Automated volume analysis

Karimi-Bidhendi *et al. J Cardiovasc Magn Reson* (2020) 22:80 https://doi.org/10.1186/s12968-020-00678-0 Journal of Cardiovascular Magnetic Resonance

#### RESEARCH



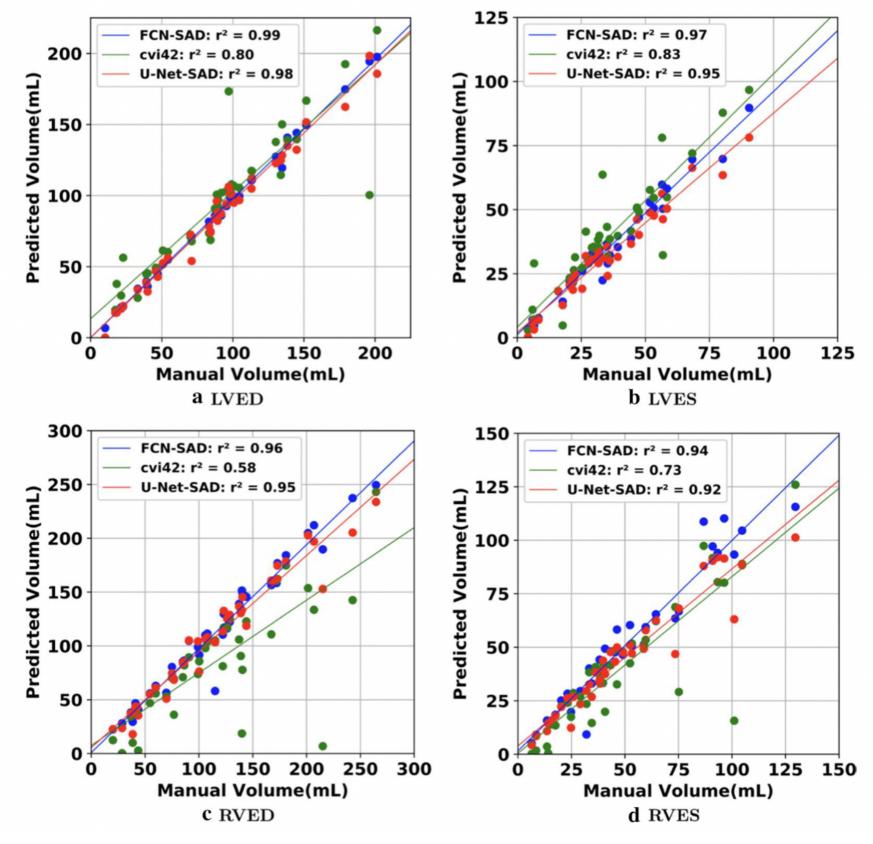


#### Fully-automated deep-learning segmentation of pediatric cardiovascular magnetic resonance of patients with complex congenital heart diseases

Saeed Karimi-Bidhendi<sup>1</sup>, Arghavan Arafati<sup>2</sup>, Andrew L. Cheng<sup>3</sup>, Yilei Wu<sup>1</sup>, Arash Kheradvar<sup>2\*</sup> and Hamid Jafarkhani<sup>1\*</sup>



#### Automated volume analysis







#### Automated volume analysis

- Conclusions The chambers' segmentation results from our fully-automated method showed strong agreement with manual segmentation and no significant statistical difference was found by two independent statistical analyses.
- Relying on these outcomes, it can be inferred that by taking advantage of generative adversarial networks (GAN), the method is clinically relevant and can be used for pediatric and congenital CMR segmentation and analysis.





#### Automated 4D flow analysis



#### **HHS Public Access**

Author manuscript

Magn Reson Med. Author manuscript; available in PMC 2021 April 01.

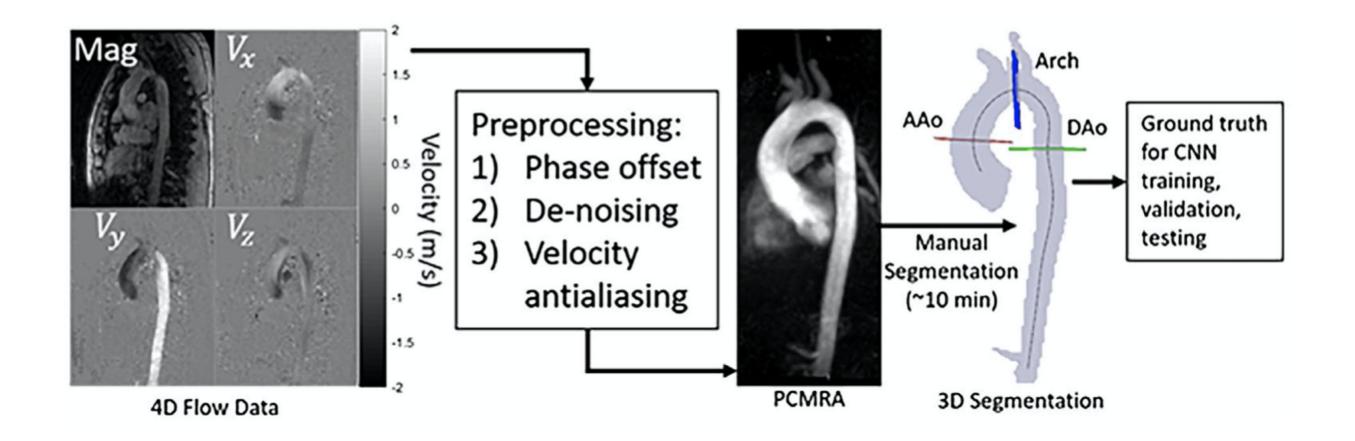
Published in final edited form as: Magn Reson Med. 2020 October ; 84(4): 2204–2218. doi:10.1002/mrm.28257.

#### Fully automated 3D aortic segmentation of 4D flow MRI for hemodynamic analysis using deep learning

Haben Berhane<sup>1</sup>, Michael Scott<sup>2,3</sup>, Mohammed Elbaz<sup>2,3</sup>, Kelly Jarvis<sup>3</sup>, Patrick McCarthy<sup>4</sup>, James Carr<sup>2</sup>, Chris Malaisrie<sup>3</sup>, Ryan Avery<sup>3</sup>, Alex J. Barker<sup>5</sup>, Joshua D. Robinson<sup>1</sup>, Cynthia K. Rigsby<sup>1</sup>, Michael Markl<sup>2,3</sup>



#### **Automated 4D flow analysis**



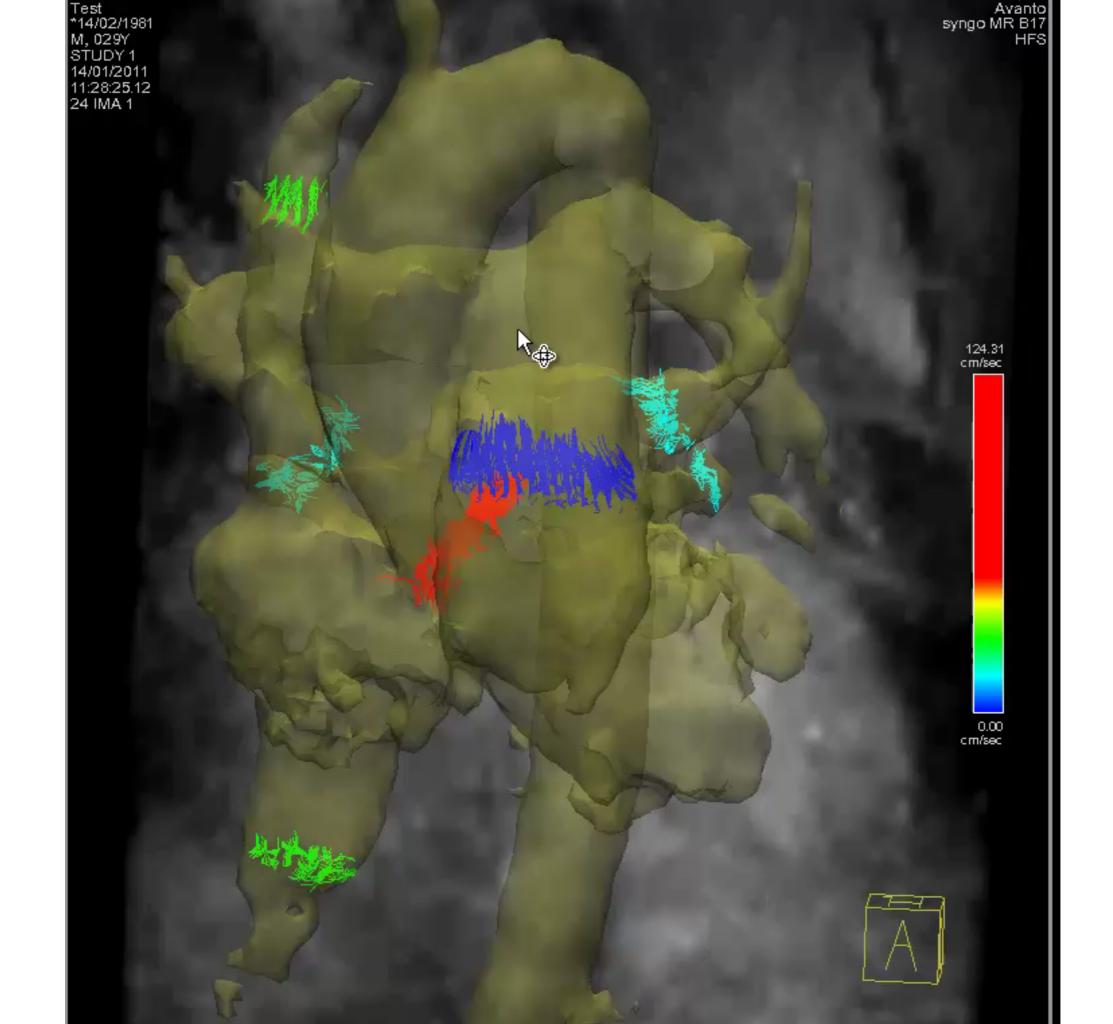




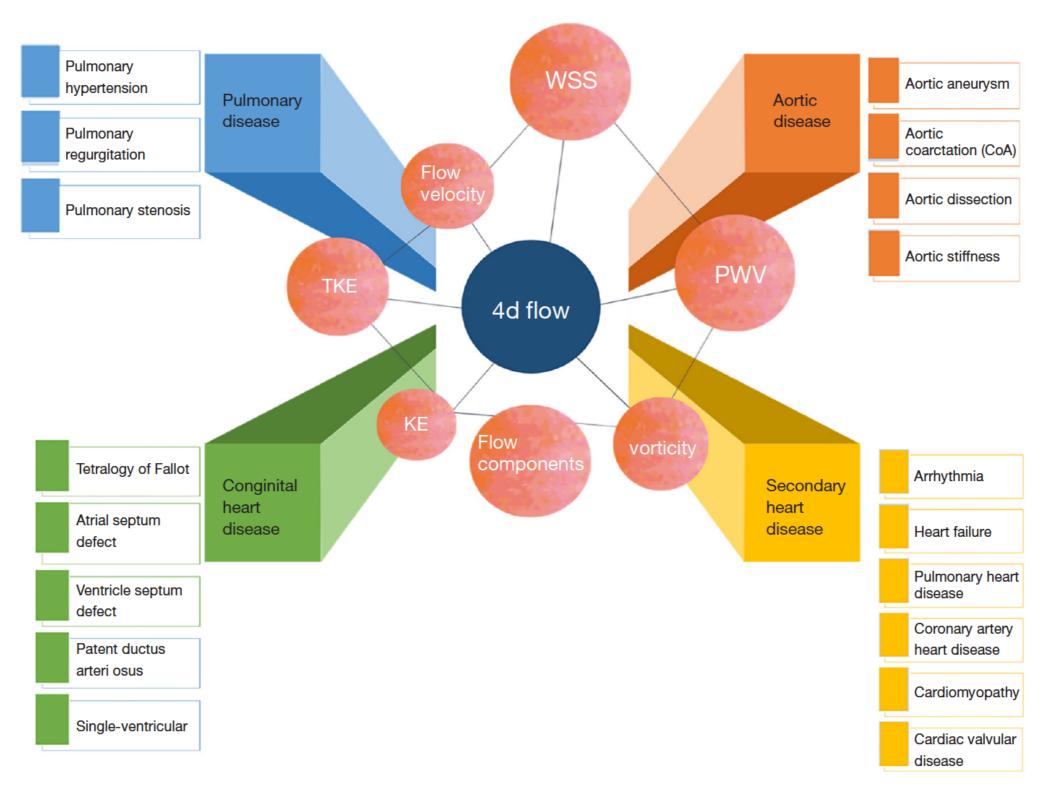
### Automated 4D flow analysis

- Aim To generate fully automated and fast 4D-flow MRI-based 3D segmentations of the aorta using deep learning for reproducible quantification of aortic flow, peak velocity, and dimensions
- Subjects 1018 subjects with aortic 4D-flow MRI (528 with bicuspid aortic valve, 376 with tricuspid aortic valve and aortic dilation, 114 healthy controls)
- **Results** Convolutional neural network segmentation required 0.438  $\pm$  0.355 s vs 630  $\pm$  254 s for manual analysis, with excellent agreement for flow, peak velocity, and dimensions





# New applications





From: Zhuang B, Sirajuddin A, Zhao S, Lu M. Quant Imaging Med Surg 2021;11(9):4193-4210.

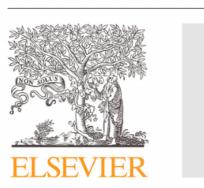


# Automated diagnosis



## **Computer-aided diagnosis**

Medical Image Analysis 26 (2015) 185–194



Contents lists available at ScienceDirect

**Medical Image Analysis** 

journal homepage: www.elsevier.com/locate/media

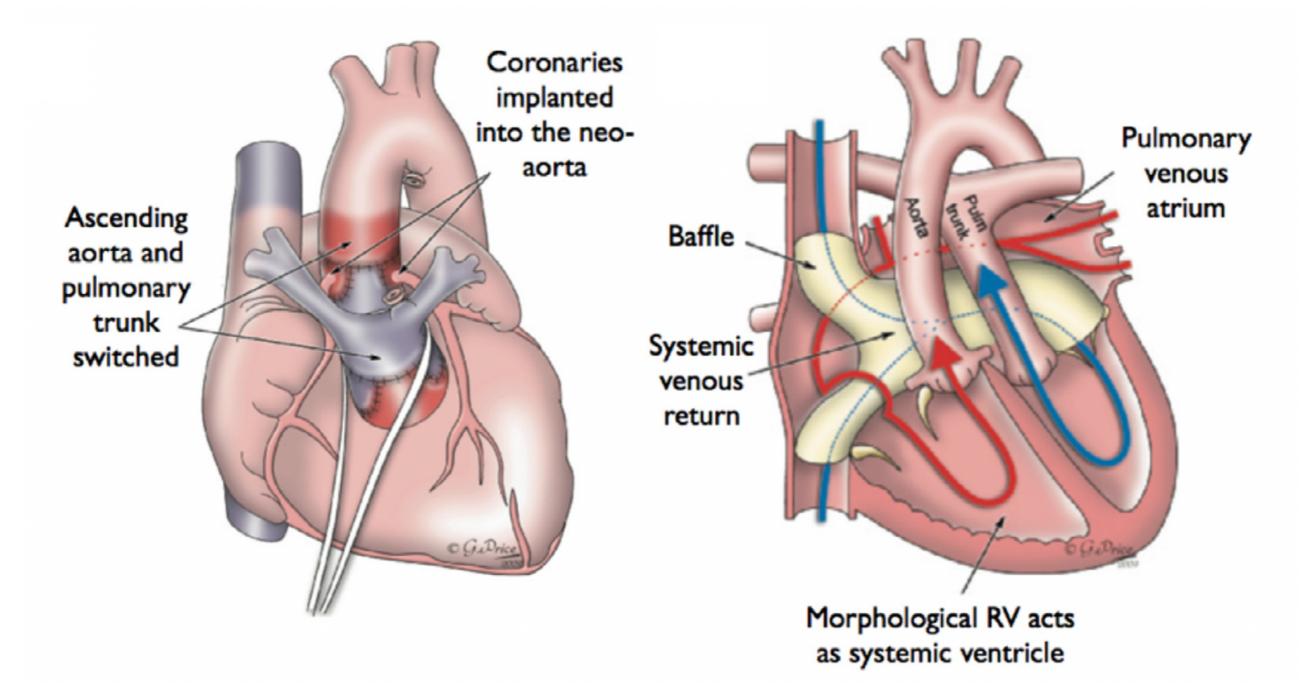
Voxelwise atlas rating for computer assisted diagnosis: Application to congenital heart diseases of the great arteries



Maria A. Zuluaga<sup>a,1,\*</sup>, Ninon Burgos<sup>a,1</sup>, Alex F. Mendelson<sup>a</sup>, Andrew M. Taylor<sup>b,c</sup>, Sébastien Ourselin<sup>a</sup>



## **TGA diagnosis**

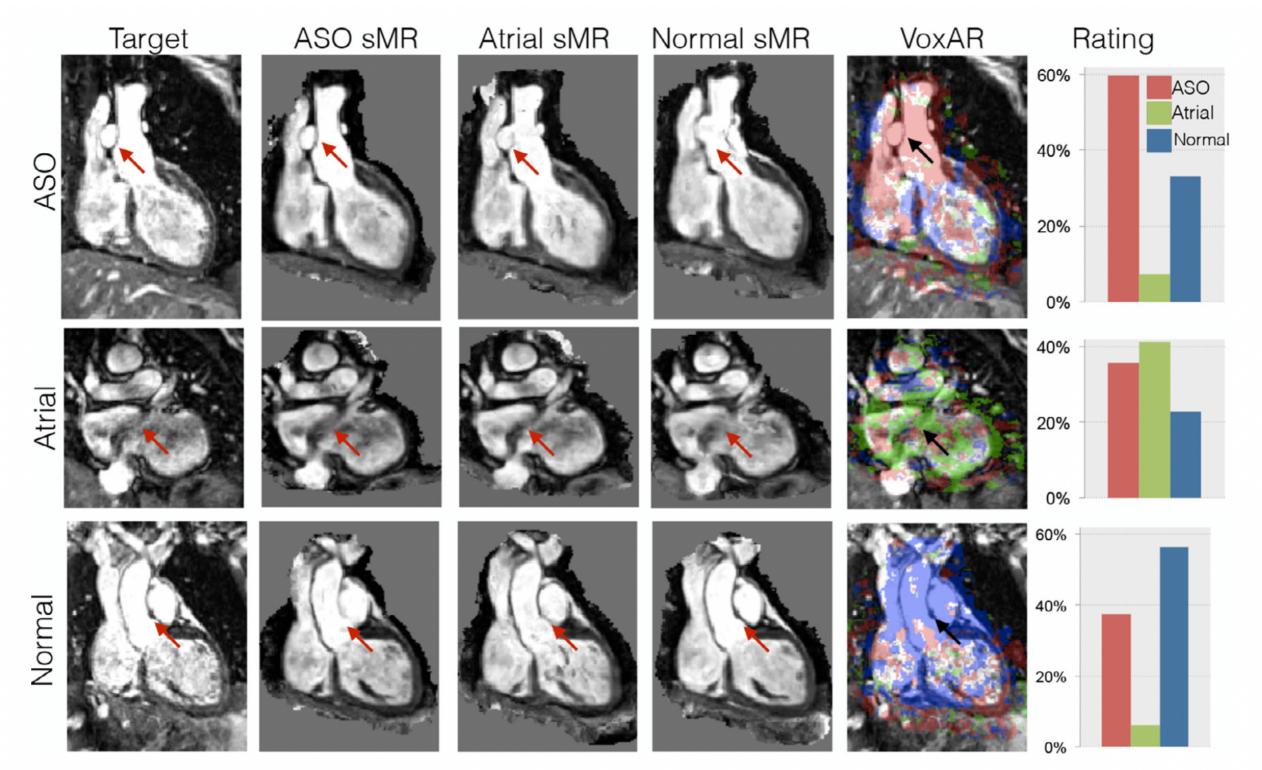


**Post arterial switch operation** 

**Post atrial switch** 



#### **Computer-aided diagnosis**



UCL



## **Computer-aided diagnosis**

- **Aim** To use atlas based analysis to define similarity between the atlas and target images. A rating map displaying for each voxel the condition of the atlases most similar to the target was defined. The final diagnosis was established by assigning the condition of the database the most represented in the rating map
- Results The proposed approach outperforms other state-of-the-art methods using annotated images, with an accuracy of 97.3% when evaluated on a set of 60 whole heart MR images containing healthy and pathological subjects using cross validation.





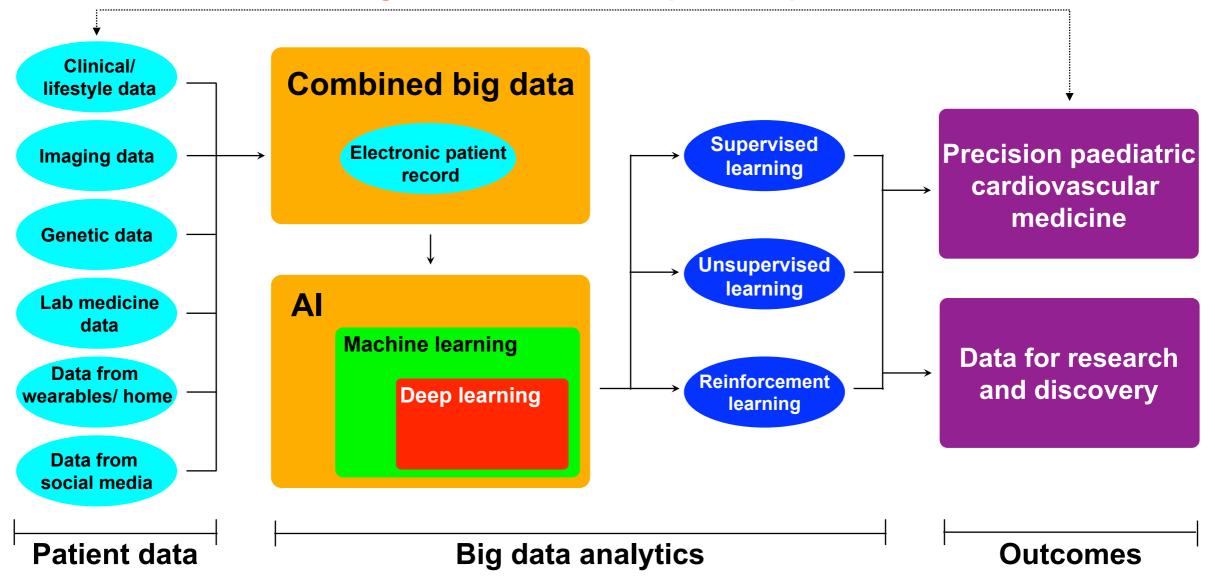
# Big data Precision medicine





# Potential for precision medicine

Big data models made patient specific







# Trusted research environment

#### Bring your data



#### Invite your multi-disciplinary team

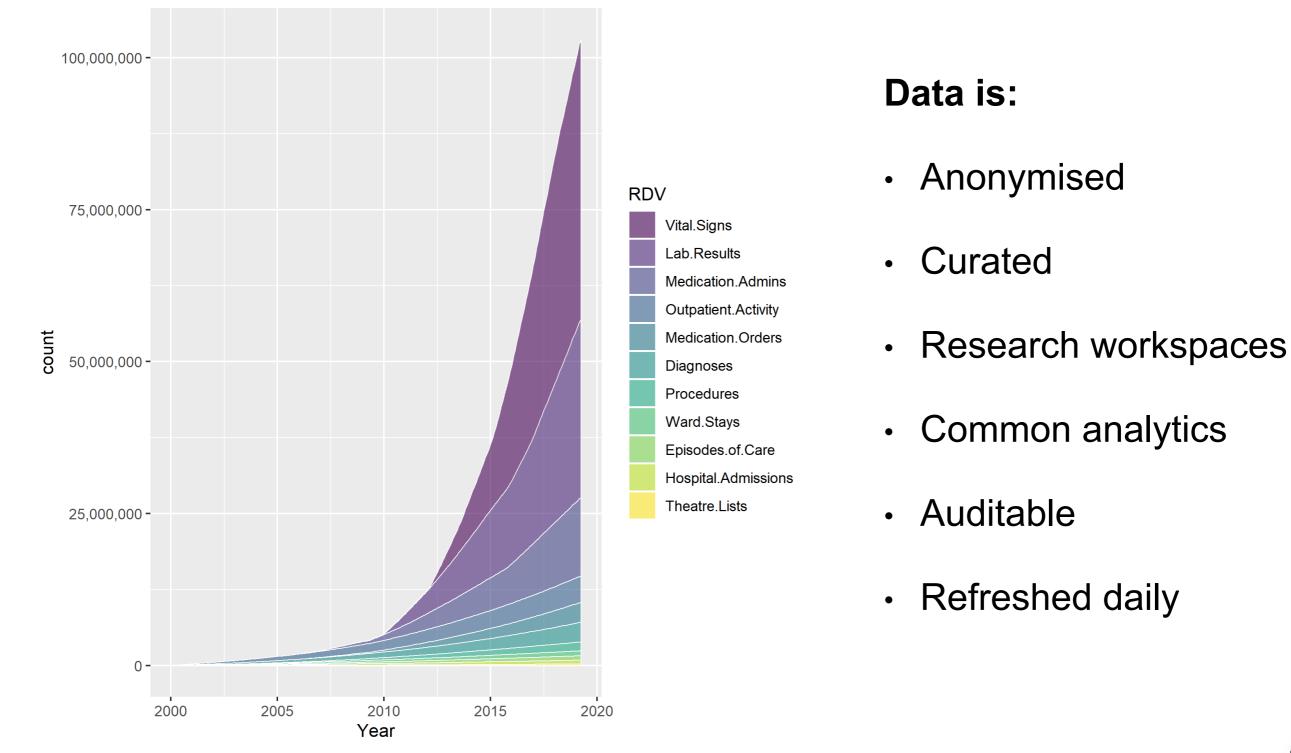






## Data in data lake

Accumulated data in the GOSH DRE Data Lake





# TRE query around lost appointments

# 18,556 appointments were missed across 2020/21

Greater than 720 weekdays (2.75 years) would be required to achieve all out-patient catch-up activity, if weekday hospital activity were able to increase by 10% with respect to pre-COVID 19 activity

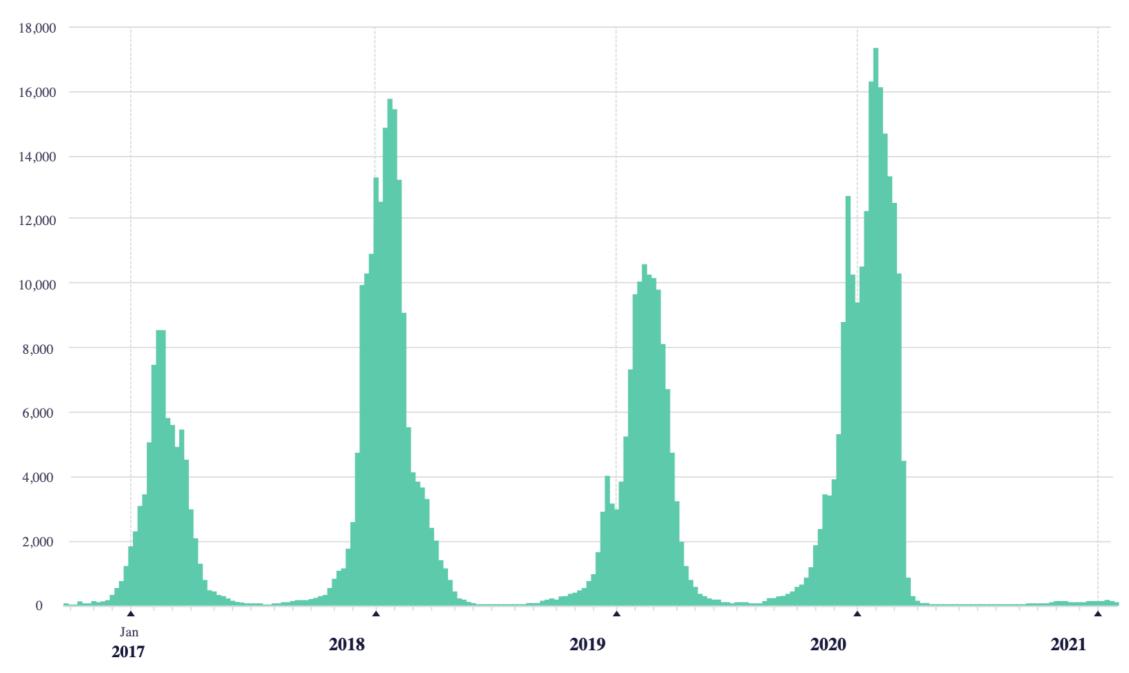




## Power of big data

Positive Influenza Lab Results (Weekly Total)

n=569,571



"Seasonal Influenza Rates Drop to Historic Lows During the COVID-19 Pandemic." 2021. Epic Health Research Network (EHRN.org)













- Change to the way care is delivered
- Build good quality (excellent data in) large data sets
- Move from single centre validation to universal applicability
- Understand data issues Confidentiality/ Ownership
- Value What is the worth of healthcare data?
- Importance of regulation for ethical use of data, but not overregulation that will stifle crucial innovation
- Importance of understanding the role of decision support tools/ models of care, and where AI information does not make sense
- Connectivity to link disparate data sets, coming from the home, primary care & the hospital setting





## Conclusions

- This field will expand significantly over the next decade
- Improving targeted patient care
- Reducing mundane tasks for radiologists
- Enhancing our diagnostic capabilities and accuracy
- By combining data from many sources this will further improve care

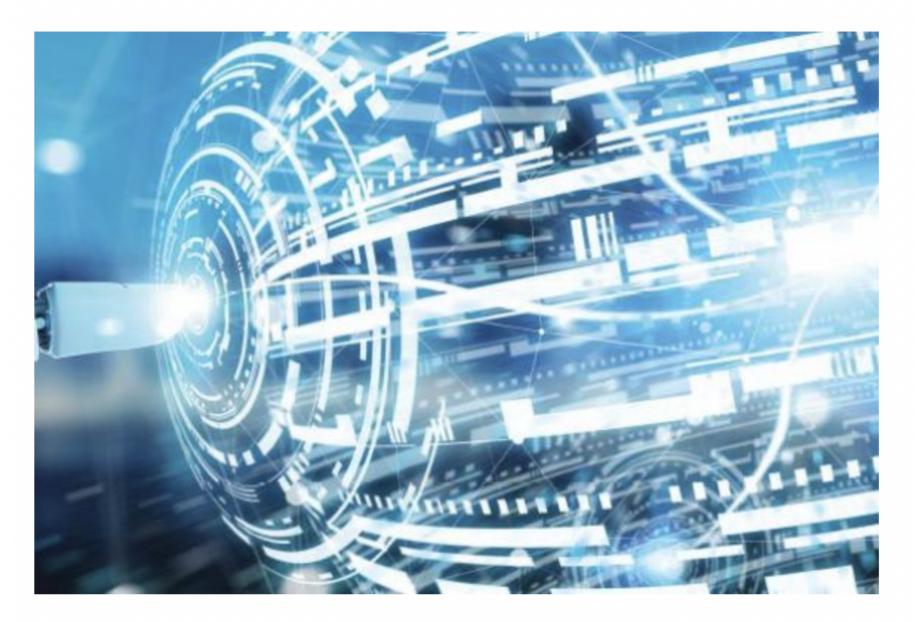
Al will drive much of this change in the next decade, though won't be a panacea for everything





#### Wait. Will AI Replace Radiologists After All?

| February 18, 2020 | Artificial Intelligence



YES. NO. MAYBE. IT DEPENDS.





"My guess is that in 10 to 20 years, most imaging studies will be read only by machines...(with)...The results transmitted directly to the referring physician without input from a human radiologist"

> "AI allows radiologists to pull information that would otherwise be left on the table...(with)...AI enhancing the value of medical imaging, which is great for patients as well as the filed of radiology"





**NHS Foundation Trust** 

#### **Any questions**

The child first and always