# RadOnc & Al methods in the real-world: *new lessons, new challenges*

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# Acknowledgements

T. PurdieP. ChungC. McIntoshM. TjongL. ConroyA. BayleyT. CraigP. WardeD. JaffrayC. CattonV. KongJ. Helou

P. Warde **M. Gospodarowicz** 







## Disclosures

I have no personal disclosures or conflicts of interest to declare

The AI method for auto planning has been licensed to RaySearch Laboratories (*Drs. Purdie and McIntosh*)



# (thought from today)



## Whatchamacallit?

- keeps the fibres of the lace from unraveling
- firmness and narrow profile that makes easier: i) to hold;
   ii) to feed through eyelets

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## Rumpelstiltskin Principle

Naming something gives you power over it.

Vocabulary / taxonomy / ontology are more fundamental than we appreciate.

## Al to Drive (RO) Clinical Initiatives

Automated Breast Planning

Protons for Paediatric Cancer

Quality

**Review Case** Rounds

Peer

RT Planning

Al Based Automated Planning

**Automated** Segmentation

Clinical Decision Making

Assurance

**Big Data** Platform

Outcome Prediction

## Al to Drive (RO) Clinical Initiatives

#### The NEW ENGLAND JOURNAL of MEDICINE

#### REVIEW ARTICLE

FRONTIERS IN MEDICINE

#### Machine Learning in Medicine

Alvin Rajkomar, M.D., Jeffrey Dean, Ph.D., and Isaac Kohane, M.D., Ph.D.

biomedical engineering

REVIEW ARTICLE

#### Artificial intelligence in healthcare

Kun-Hsing Yu<sup>1</sup>, Andrew L. Beam<sup>1</sup> and Isaac S. Kohane<sup>1,2\*</sup>

Artificial intelligence (AI) is gradually changing medical practice. With recent progress in digitized data acquisition, machine learning and computing infrastructure, AI applications are expanding into areas that were previously thought to be only the province of human experts. In this Review Article, we outline recent breakthroughs in AI technologies and their biomedical applications, identify the challenges for further progress in medical AI systems, and summarize the economic, legal and social implications of AI in healthcare.

#### REVIEW ARTICLE | FOCUS

medicine

#### High-performance medicine: the convergence of human and artificial intelligence

Eric J. Topol O

The use of artificial intelligence, and the deep-learning subtype in particular, has been enabled by the use of labeled big data, along with markedly enhanced computing power and cloud storage, across all sectors. In medicine, this is beginning to have an impact at three levels: for clinicians, predominantly via rapid, accurate image interpretation; for health systems, by improving workflow and the potential for reducing medical errors; and for patients, by enabling them to process their own data to promote health. The current limitations, including bias, privacy and security, and lack of transparency, along with the future directions of these applications will be discussed in this article. Over time, marked improvements in accuracy, productivity, and workflow will likely be actualized, but whether that will be used to improve the patient-doctor relationship or facilitate its crosion remains to be seen.

#### Main take home messages

## Still far from clinical realm (many retrospective/simulation approaches)

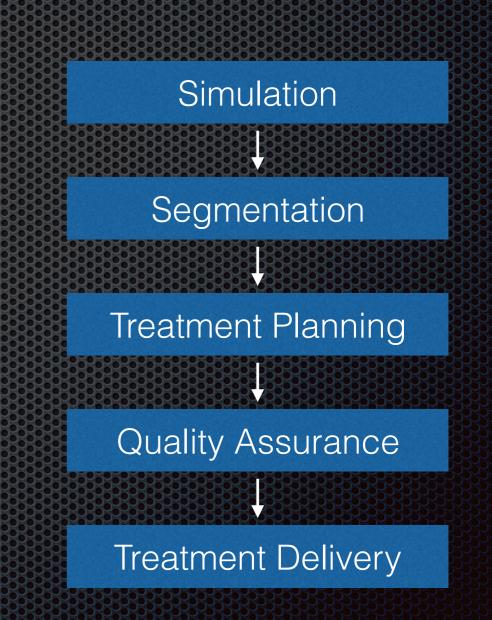
#### **Unquantified** value/impact

## Simple (and biased) RadOnc view



## Why aiming for automation in RO?

- We are nerds obsessed with Tech
- Limited (RT) resources, various (RT) tasks are quite resource intensive
- Operator's time and expertise impact quality
- Many processes are not 'standard'(izable?)
- The value of good radiotherapy
- Moore's Law
- Global impact, can we (practically) share expertise?
- Al is a sexy topic = Automatic Investment

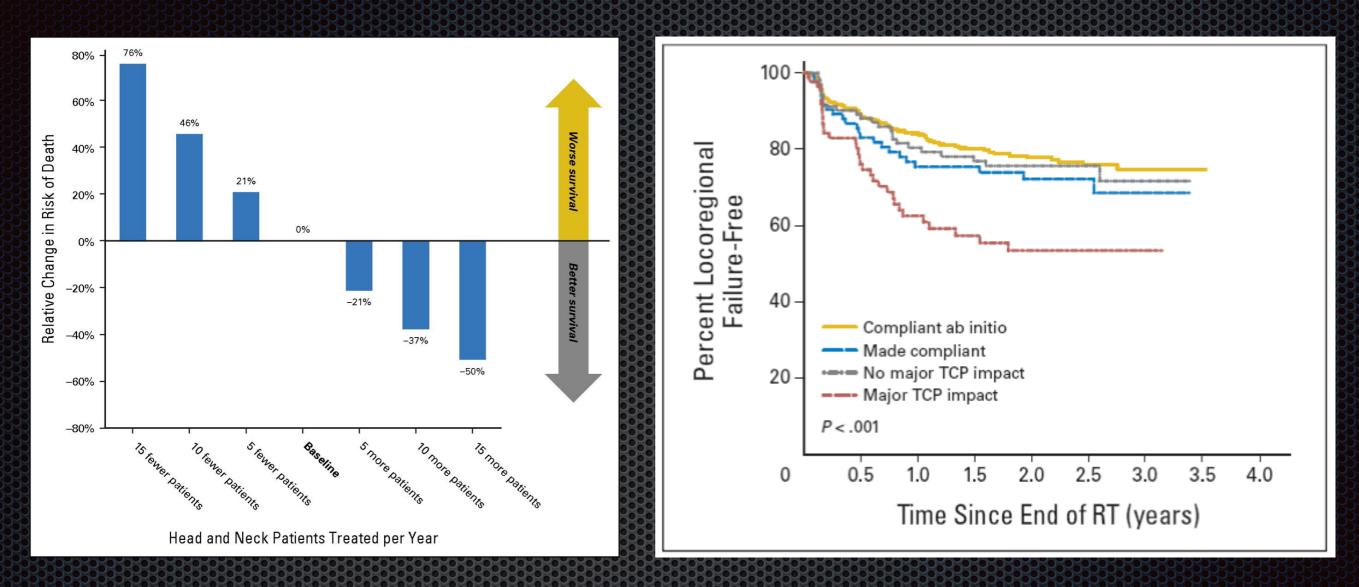


## Why aiming for automation in RO?

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## Will automation have good ROI ?

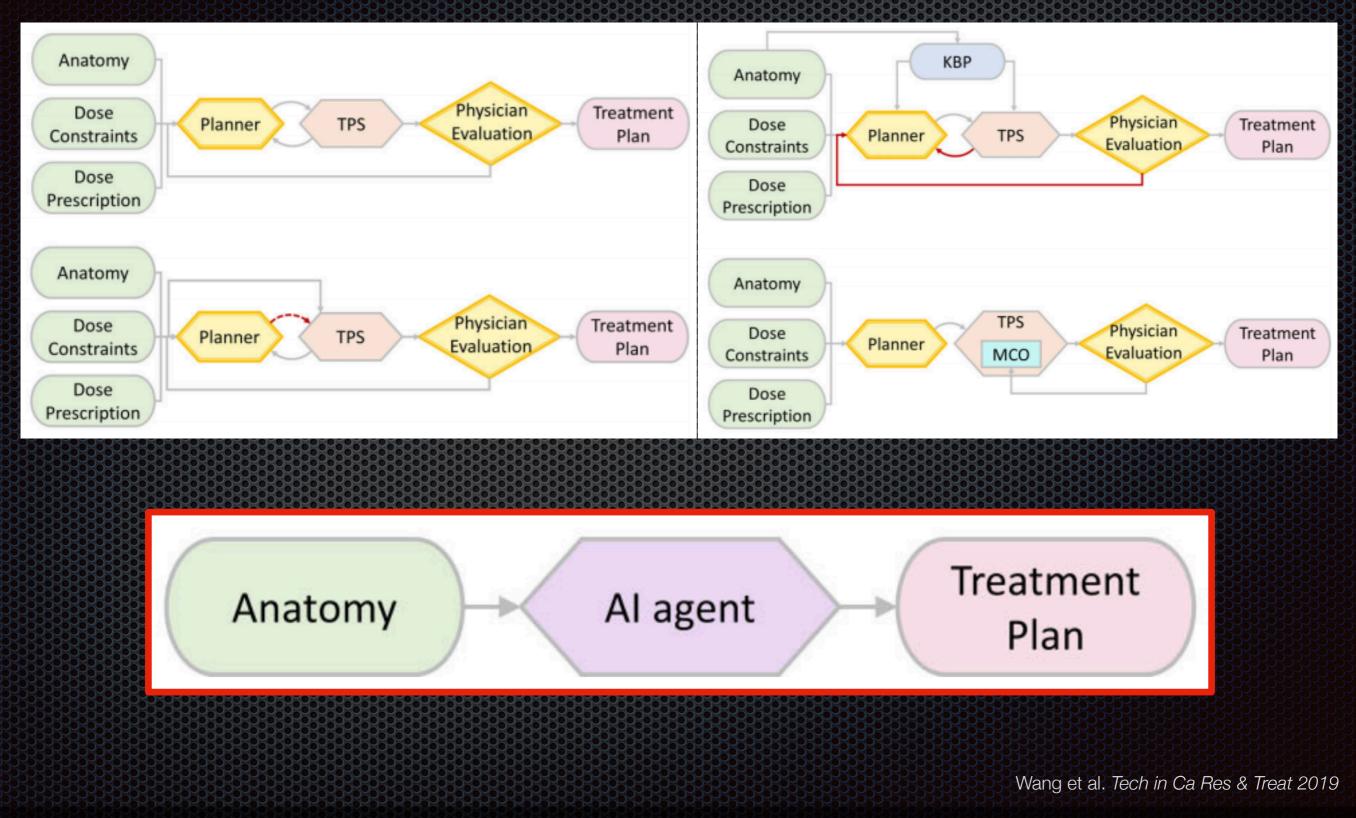


"The value of good radiotherapy is substantially greater that the incremental gains that have been achieved with new drugs and/or biologics"

Boero et al. JCO 2016; Peters et al. JCO 2010

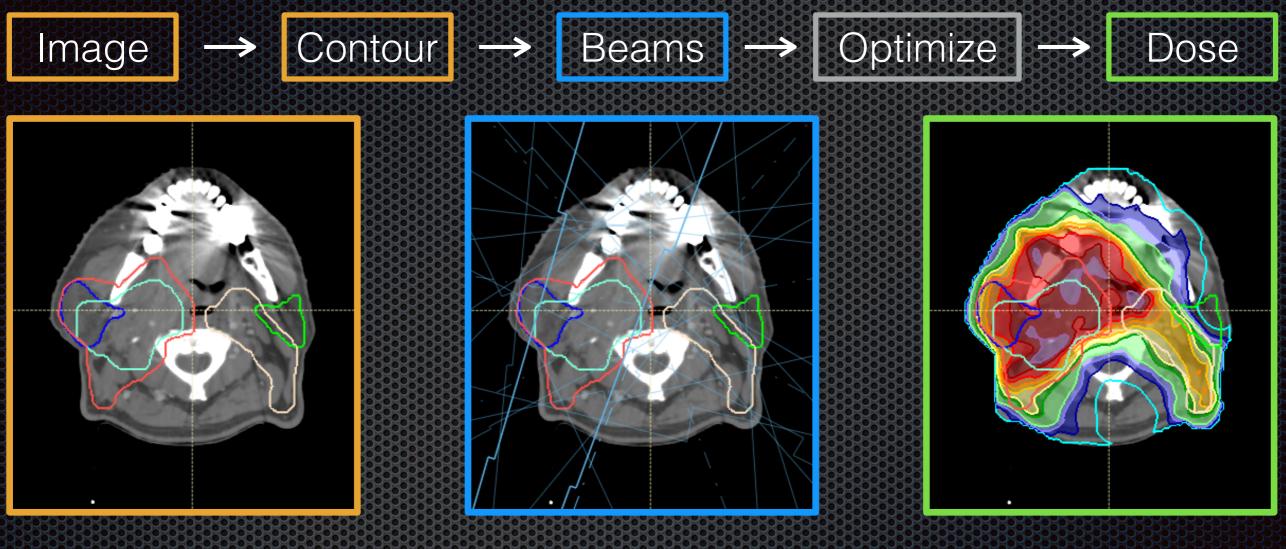
RadOnc & AI applications

# Autoplanning approaches



# Al Planning Framework

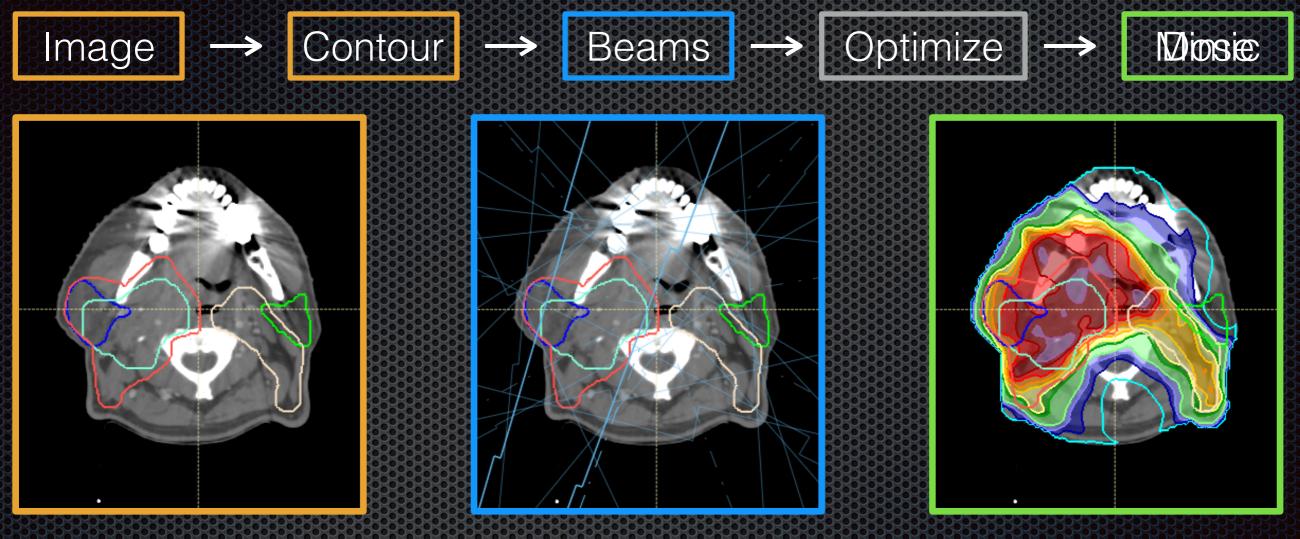
## Conventional planning pipeline:



McIntosh C, Purdie TG. IEEE TMI 2015

# AI Planning Framework

## Automated planning pipeline:



Conventional planning pipeline:

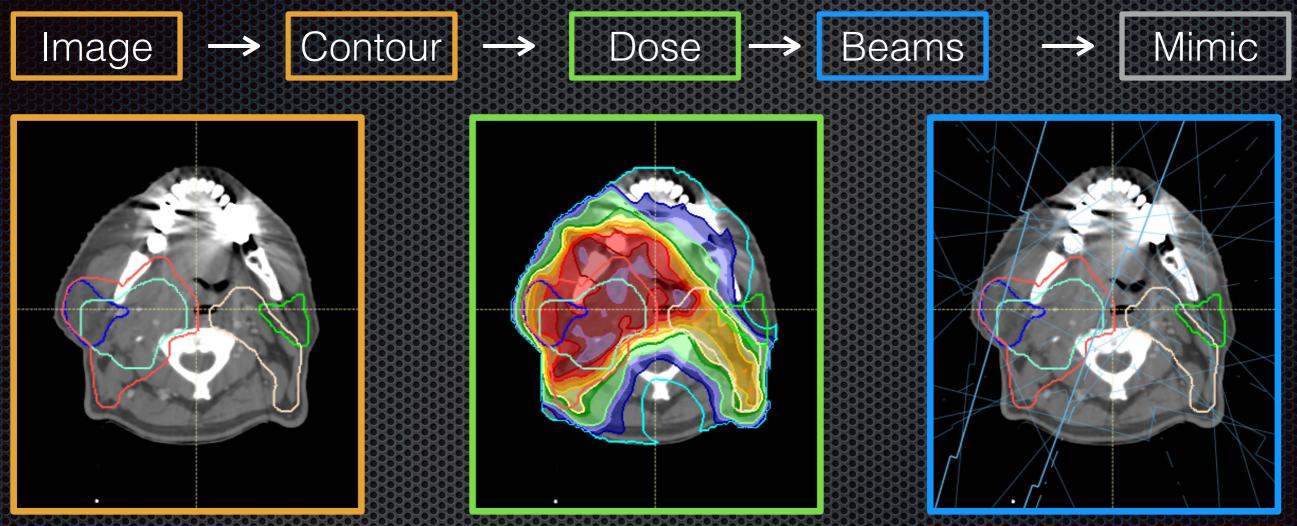
Image 
$$\rightarrow$$
 Contour  $\rightarrow$  Beams  $\rightarrow$  Optimize  $\rightarrow$  Dose

14

McIntosh C, Purdie TG. IEEE TMI 2015

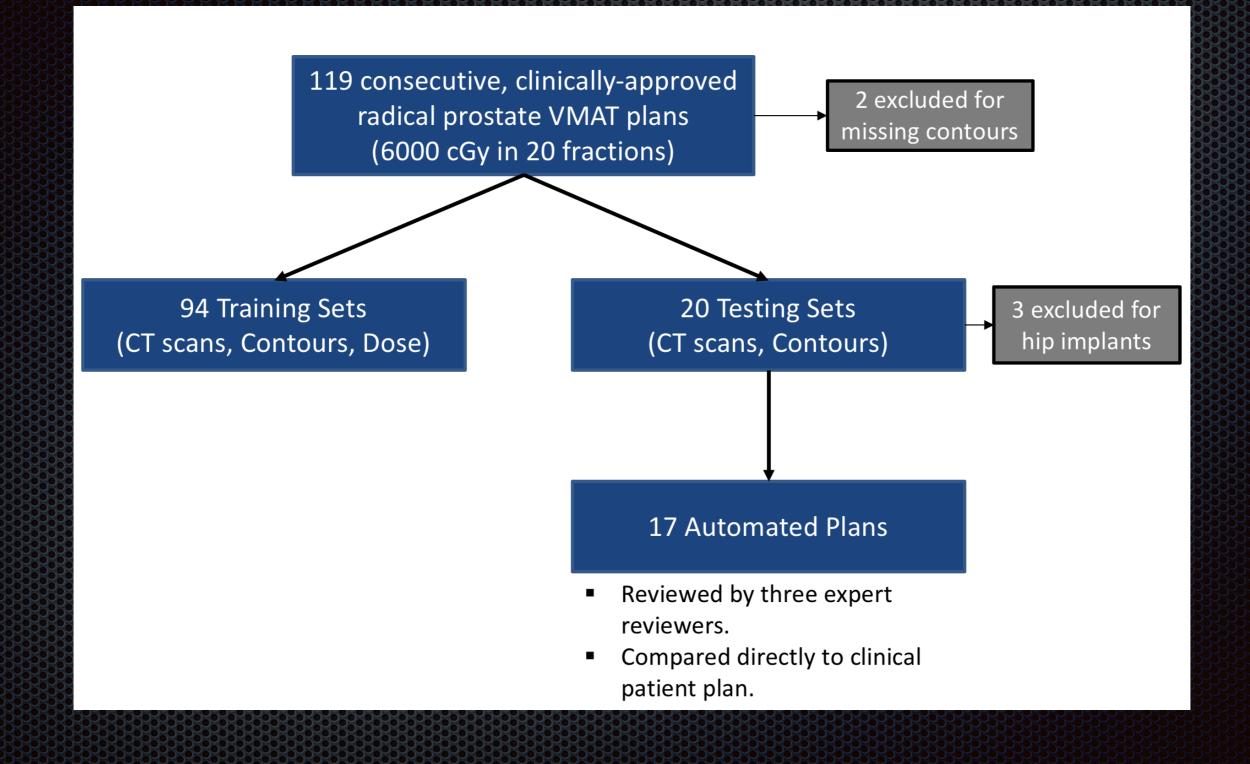
# Al Planning Framework

## Automated planning pipeline:

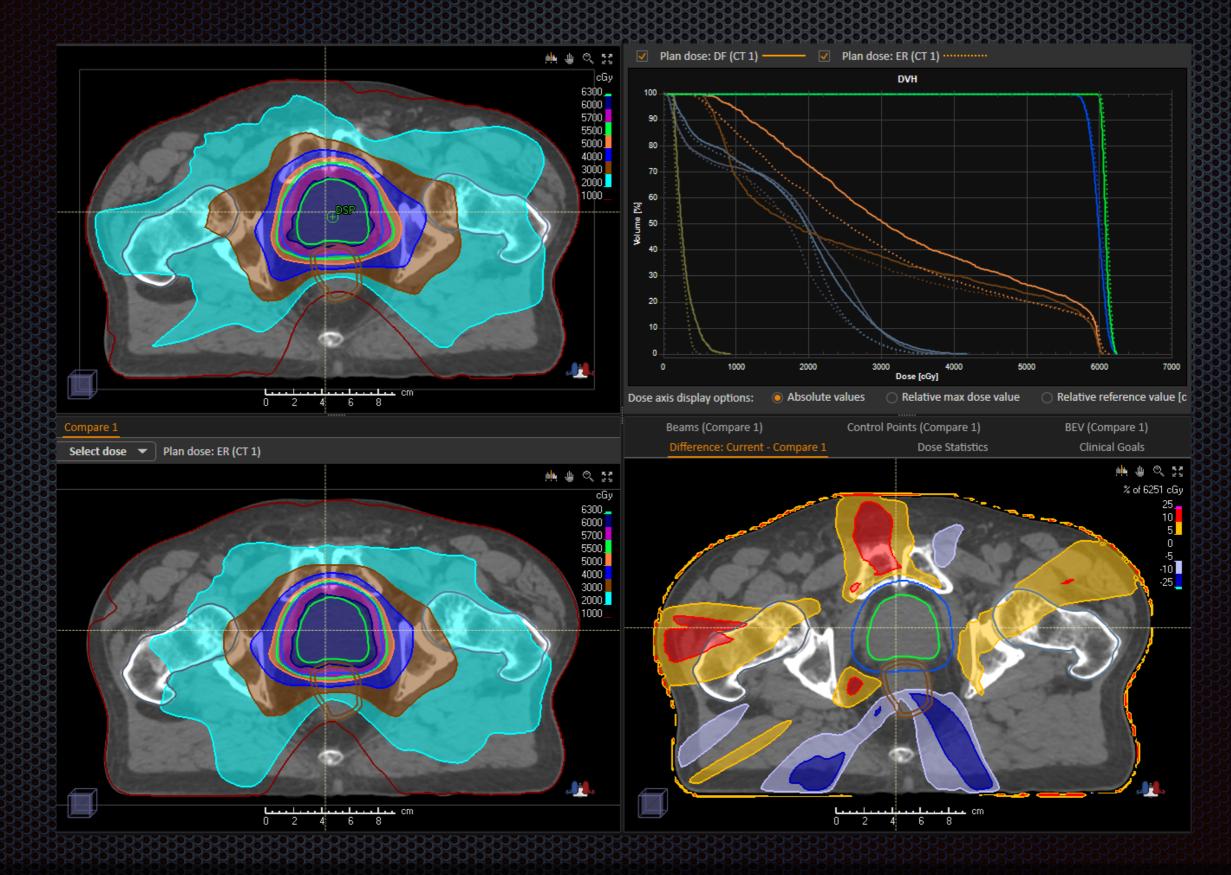


- Learn relationship of image features and patient geometry to infer dose distributions → Spatial Dose Objective
- Complete and deliverable treatment plans without:
  - defining or specifying optimization objectives
  - iterative (manual or automatic) planning steps

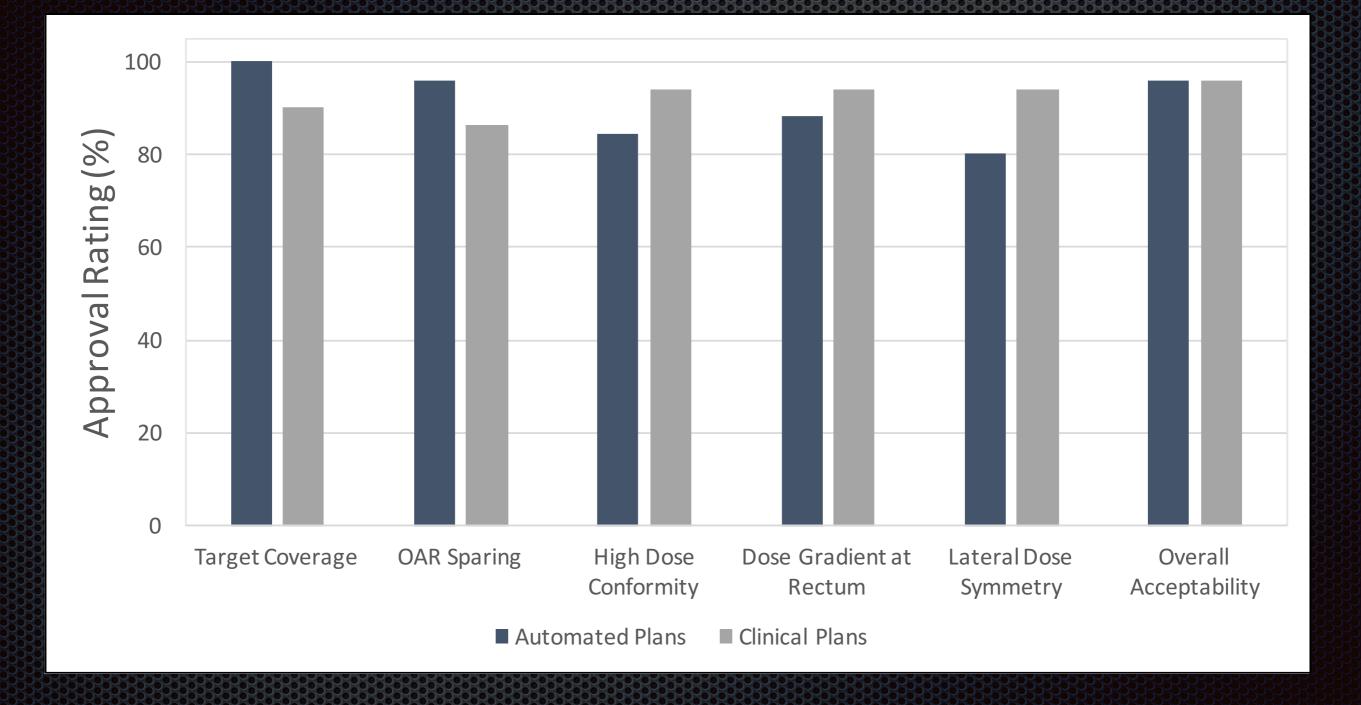
## Evaluation of (clinical) performance: Step 1



## The AI method output



## Passing the (high) bar



## The exciting result of Step 1

Image: Automated Equivalent Clinical       A       M       Equivalent Clinical         Image: Automated Equivalent Clinical       B       M       M       M       M         Image: Automated Equivalent Clinical       C       M       M       M       M         Image: Automated Equivalent Equiva						Patient		Reviewer	•	Majority Decision
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## Step 1 - Lesson 1

Thank you for submitting your manuscript to the Red Journal. It has been read and discussed by the senior editorial team who, unfortunately, did not feel it met our criteria for publication and their thoughts are appended below. They did, however, think that it may be a good fit for our sister publication "Practical Radiation Oncology". If you are interested, we would like to suggest that you take advantage of the article transfer service that both journals participate in. This gives you the option to have your manuscript files transferred directly, and removes the need for you to resubmit and reformat your manuscript.

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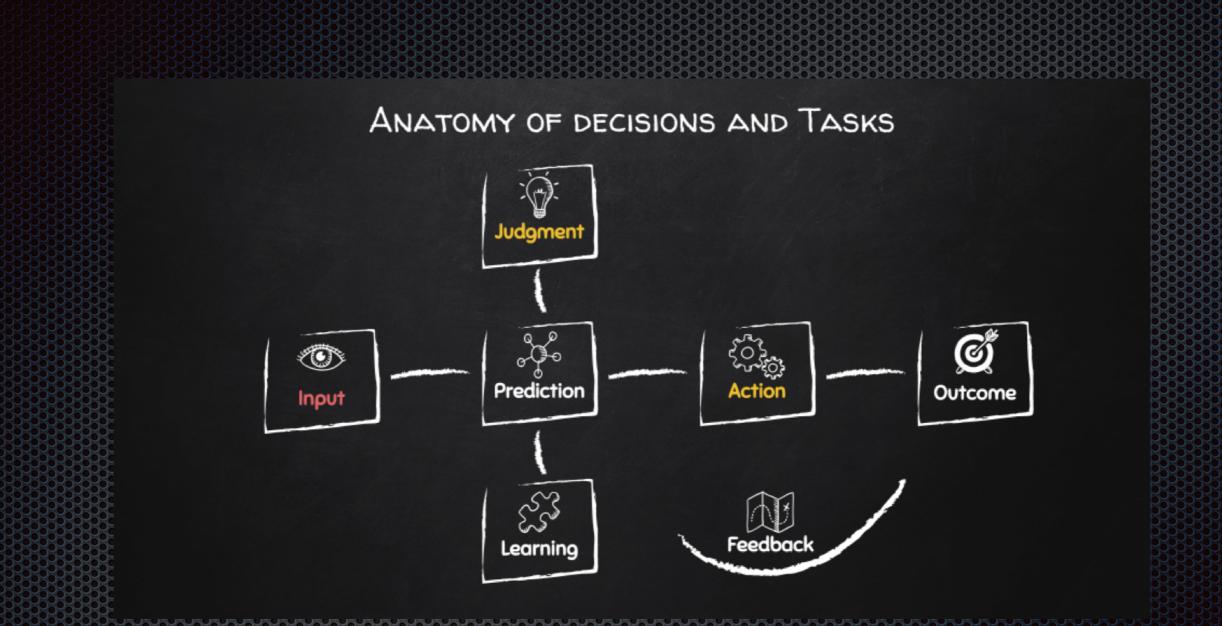
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Yours sincerely,

Anthony L. Zietman, MD Editor-in-Chief International Journal of Radiation Oncology\*Biology\*Physics

#### Value-proposition (was) unclear

## What we want (should!) evaluate ?



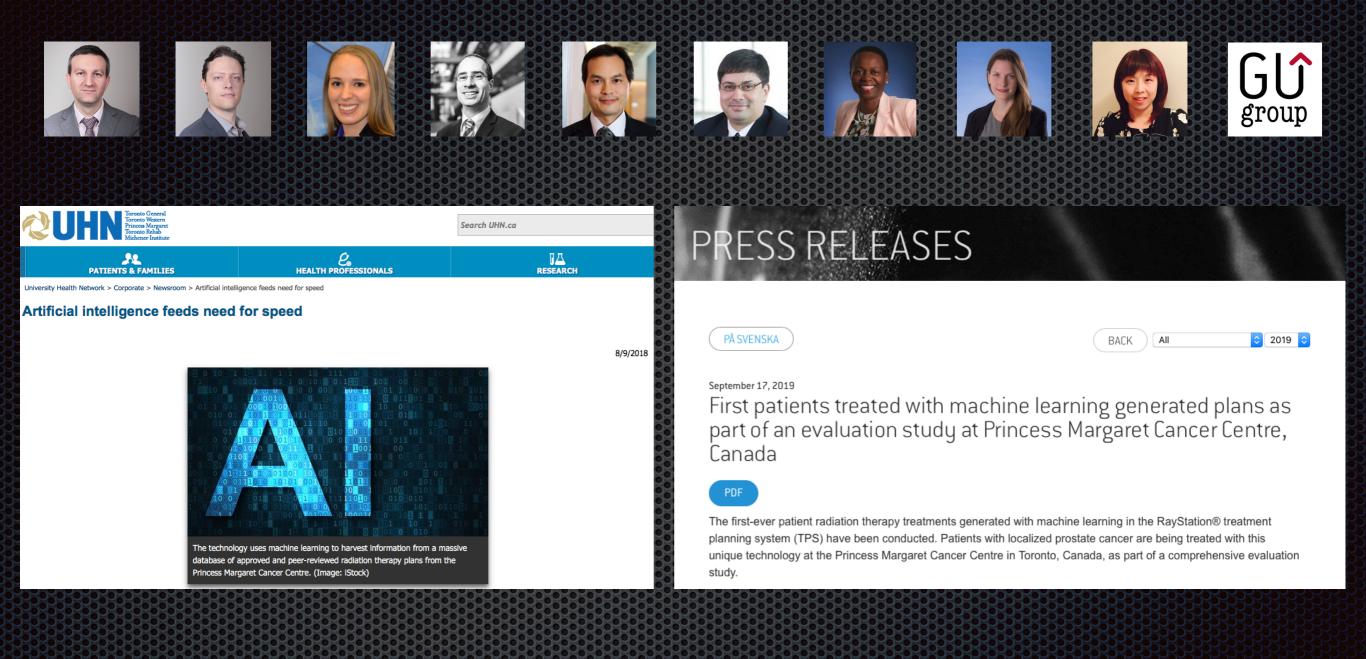
Predict a dose distribution expected to be judged favourably (e.g. approved/liked) by treatment team experts

Adapted from 'Prediction Machines' - Agrawal, Gans, Goldfarb

## Step 2 - Real World

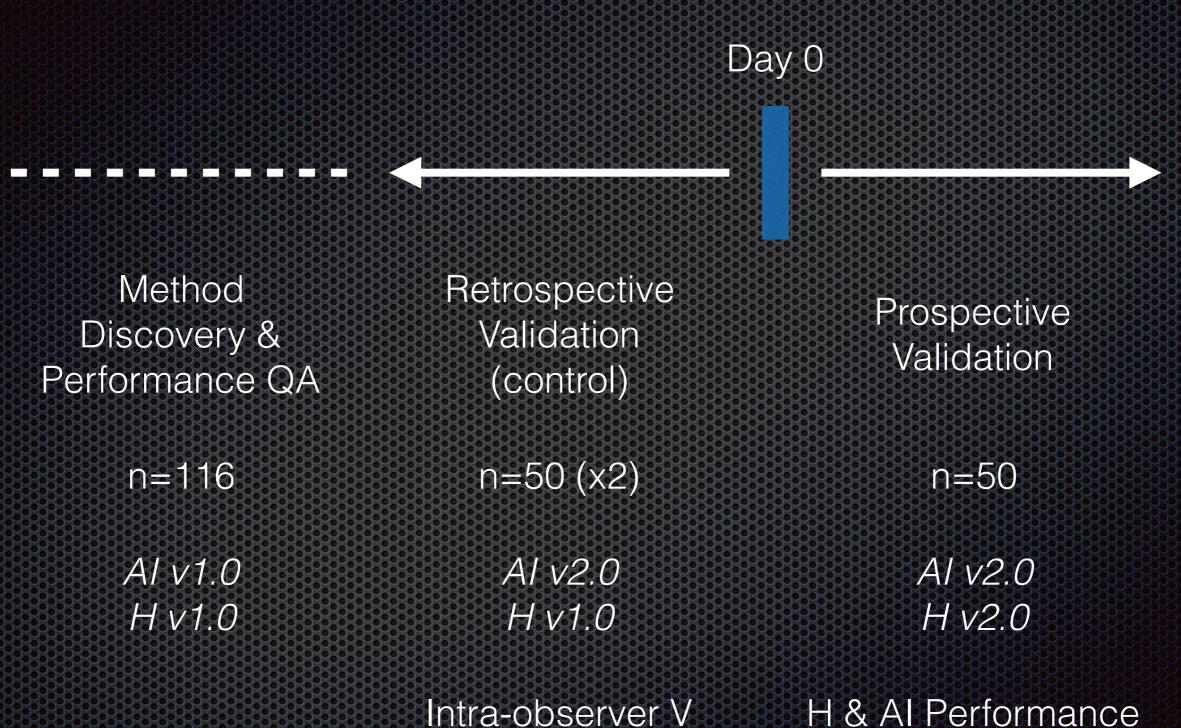


## Magic ingredienTs: Team & Trust (...and Tenacity)



"The AI plan was deemed superior for that specific patient, and got the 'green light' after meeting all our protocol and quality assurance metrics"

# Mapping our (ongoing) road



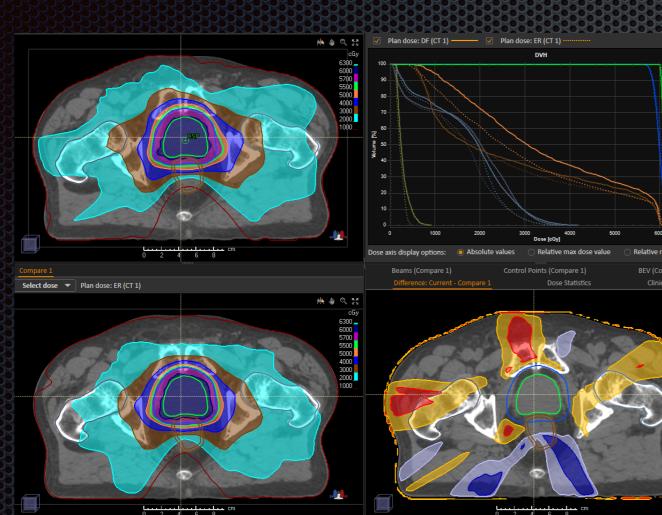
H & AI Performance

QA, Peer-review

## Every patient coming through the doors ...

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RadOnc & AI applications

#### Prostate AutoPlanning Evaluation

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Patient	υ	(F)	151	a,	aigns	or	MBN	onry)	1-

Reviewer

Plan Comparison. Which plan has better: \*

	Prostate_A1	Prostate_A2	They are Equivalent
Target Coverage	0	0	0
OAR Sparing	0	0	0
High Dose Conformity	0	0	0
Rectal Dose Gradient	0	0	0
Lateral Dose Symmetry	0	0	0

#### Plan Acceptability\*

	Acceptable	Unacceptable
Prostate_A1	0	0
Prostate_A2	0	0

#### Preferred Plan\*

	Preferred Plan
Prostate_A1	0
Prostate_A2	0
Equivalent -> go with Prostate_A1	0
Equivalent -> go with Prostate_A2	$\bigcirc$
Do not like either plan	<ul> <li>O</li> </ul>

#### Which plan do you think is the Automated Plan? \*

## Preliminary Results

Day 0

%	Human	AI	Equivalent			
Target Coverage	4 %	22 %	74 %			
OAR Sparing	16 %	66 %	18 %			
High D Conformity	40 %	18 %	42 %			
<b>Rectal Gradient</b>	20 %	66 %	14 %			
Symmetry	16 %	48 %	36 %			
Acceptable?	98 %	90 %				
Preferred	26 %	74 %				
n = 50						

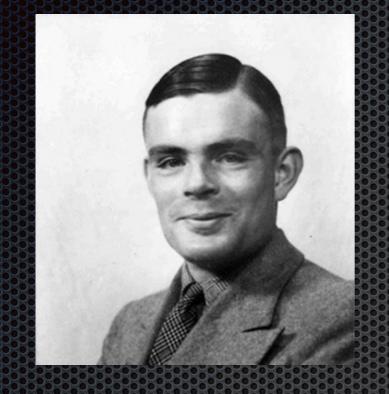
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Symmetry	16 %	48 %	36 %
Acceptable?	98 %	90 %	
Preferred	26 %	74 %	

## n = 38

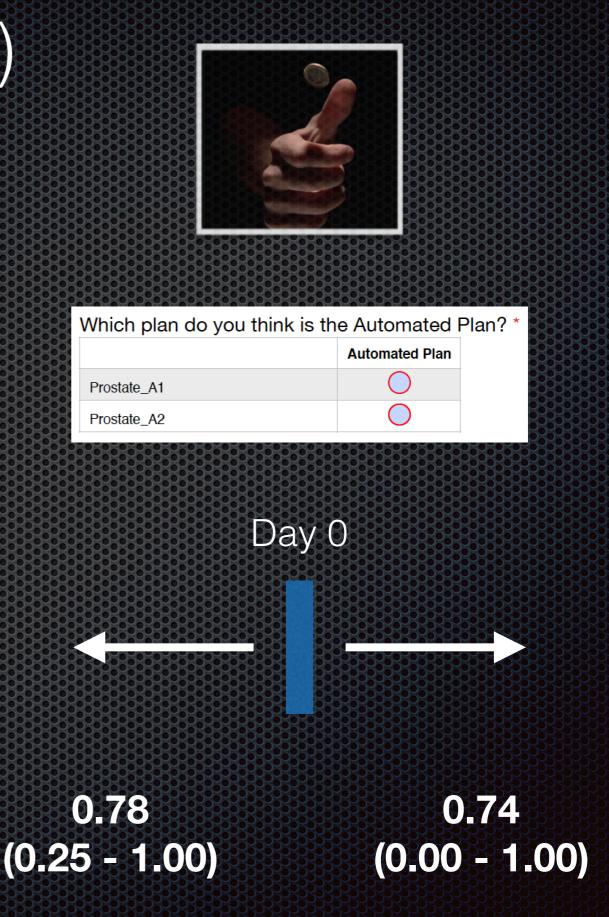
Berlin | Kingston Health Sciences Centre | 03-Feb-2020

# Preliminary Results (2)

## Alan Turing (1912-1954)



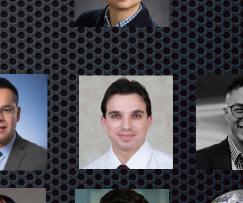
"I believe that at the end of the century the use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted."



## Future Roads

- Integration of auto-planning with MR-based auto-segmentation
- Expand to other GU treatment scenarios
- International collaboration to evaluate judgment/assessment/acceptability of AI plans
   Paving road to international applications
- Collaboration to assess performance in Phase III trial cohort
  - Model impact of true standardized planning
  - Outcome-based AI planning?







# Future Highway!

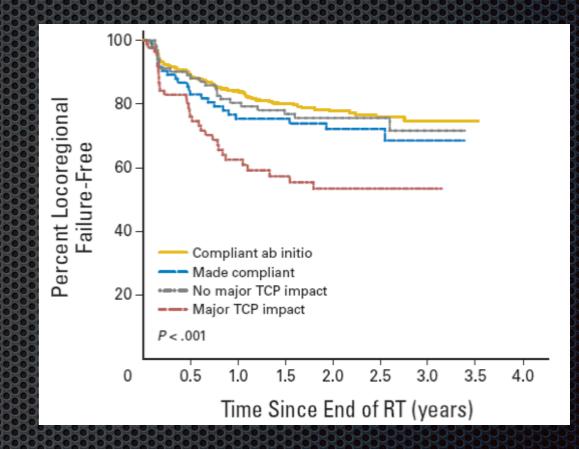


- Challenge: Drug + RT
  - Consistency
  - Quality

Education



# Evaluation phase



AI planning/QA methods could be leveraged to develop a R-GMP framework

# Summary & Thoughts

- Automation will be an essential component for many radiotherapy processes.
- The development and ascertainment of Al/automation methods deepens need for team / multi-professional approaches.
- Robust methods are necessary but insufficient to change, impact or even enter clinical practice.
  - Value: Outcomes / Cost ... Performance of method might be a surrogate.
- Principles remain principles: Start with the problem, then method, its role and value proposition.
- Prospective validation is where the value resides: lessons, challenges and opportunity to lead the field.



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