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Artificial Intelligence in treatment planning: How to move forward?

Laurence Court
lecourt@mdanderson.org
@LaurenceECourt

ESTRO-AAPM symposia on the adoption of artificial intelligence in clinical radiotherapy practice, AAPM 2020

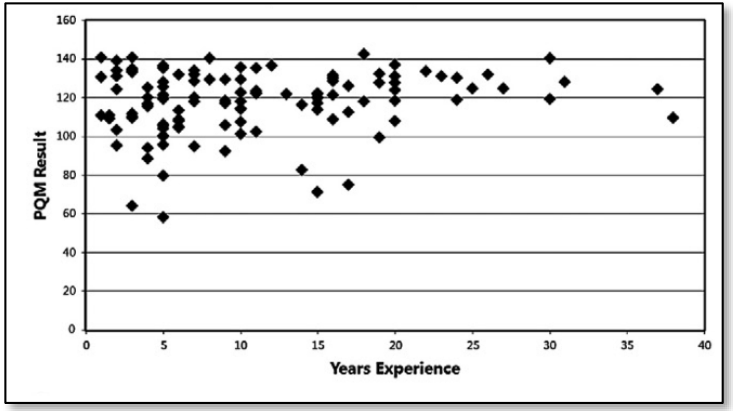
Funding / conflicts of interest

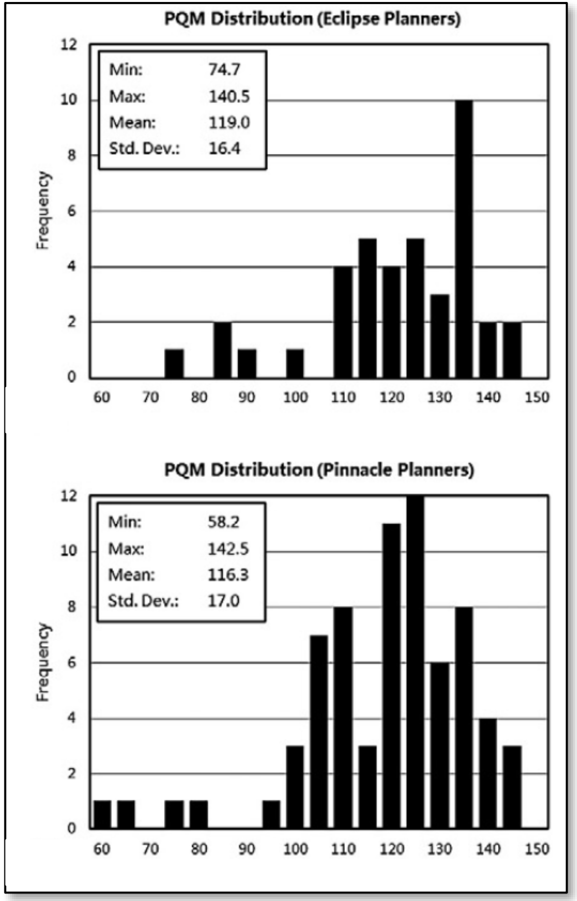
Much of my understanding of this topic has come from our development of the Radiation Planning Assistant – rpa.mdanderson.org

- National Cancer Institute (Affordable Cancer Technologies)
- Wellcome Trust (digital technologies innovator – palliative treatments)
- Cancer Prevention & Research Institution of Texas
- Varian Medical Systems
- University of Texas MD Anderson Cancer Center

We all know that different treatment planners give different treatment plans

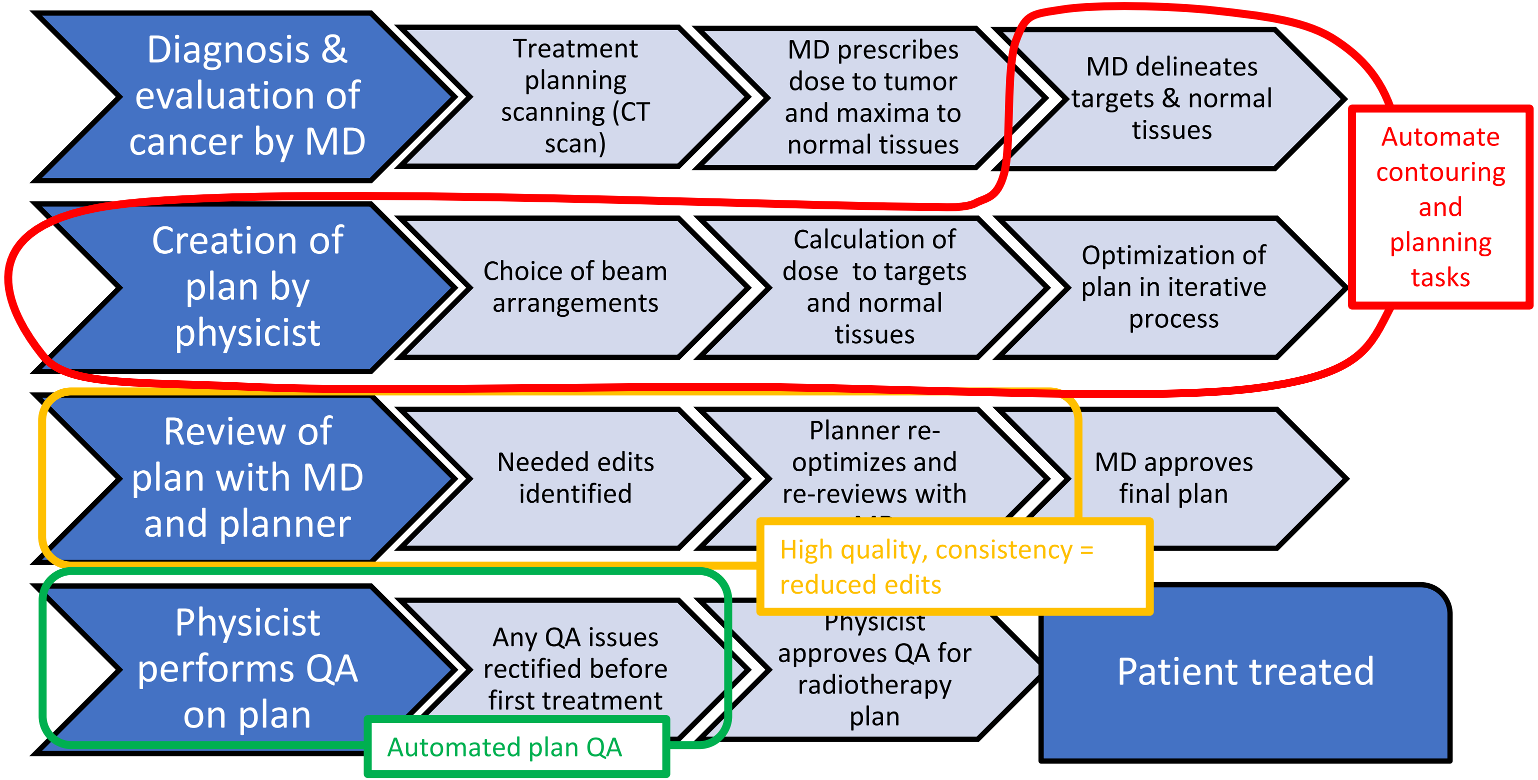
- Nelms et al 2011 analyzed 125 plans
- Defined plan quality using a “Plan Quality Metric”
- Found a very wide variability in plan quality
- No or negligible relationship between plan quality and technical parameters or planner demographics





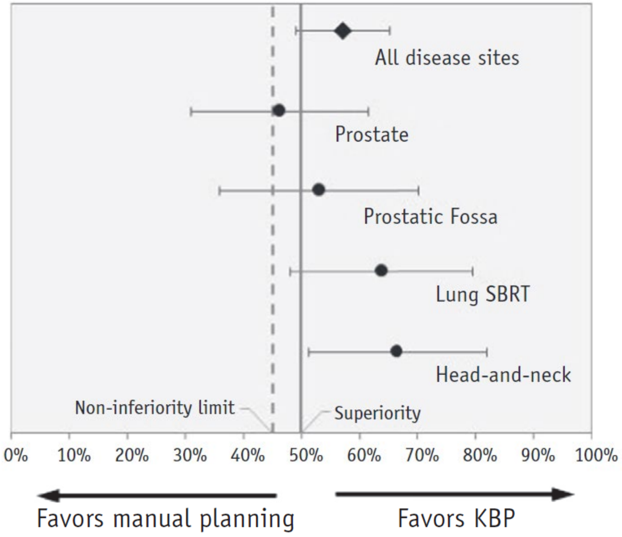
Nelms et al PRO 2011

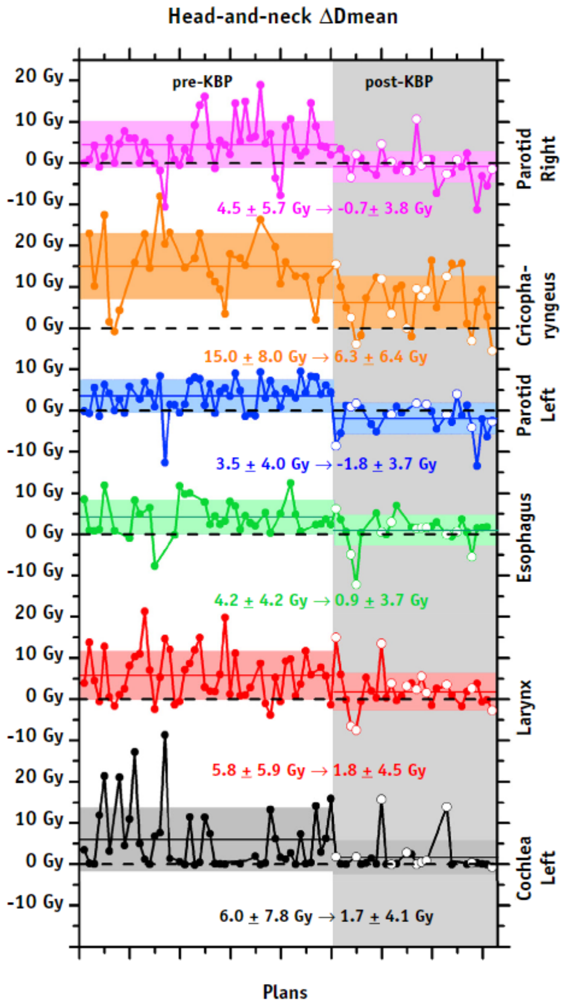
We also know that the radiotherapy planning process is complex…….



AI can give high quality VMAT plans

- Various AI approaches to plan optimization
- e.g. knowledge-based planning has been shown to be highly competitive with human planners
- Moore’s group developed KBP plans for prostate, prostatic fosa, hypofractionated lung, and head and neck





Cornell et al
IJROBP 2020

But will an automated plan from one institution be accepted at another?

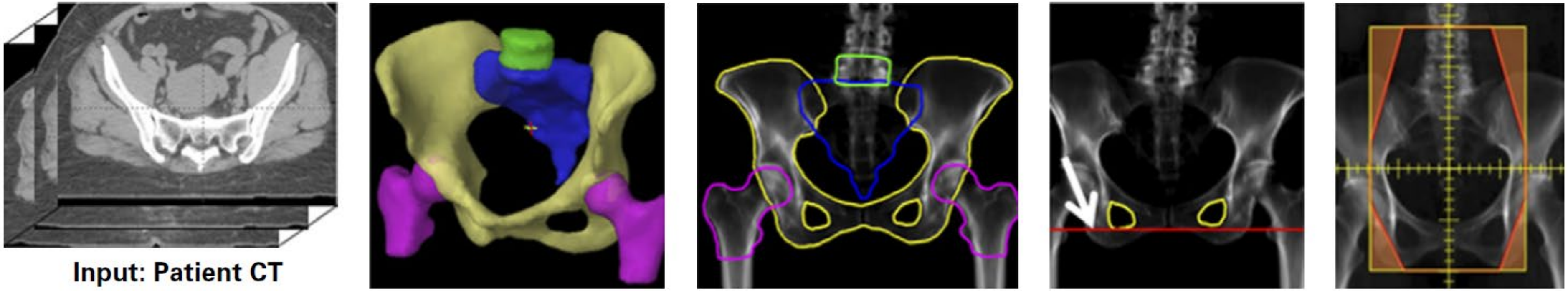
- 60 head & neck plan reviews, 14 radiation oncologists (each from a different institution)

Physician score	Clinical plan (N=60)		RPA autoplan (N=60)	
A. Acceptable as-is	45% (n=27)	78%	48% (n=29)	88%
B1. Prefer minor edits, but would use this plan if necessary	33% (n=20)		40% (n=24)	
B2. Clinically acceptable, but I would require minor edits	15% (n=9)		10% (n=6)	
A. Clinically unacceptable	7% (n=4)		2% (n=1)	

	Number of plans
Select clinical plan	16
Select RPA autoplan	28
Either plan is reasonable	15
Neither plan is reasonable	0

Adenike Olanrewaju

What about AI for traditional techniques?

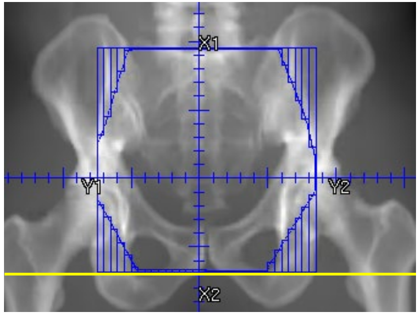


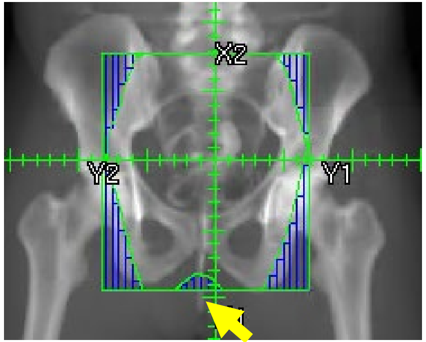
Segment bony anatomy using multiatlas deformable registration. → Project these 3D segmentations into the 2D plane of the BEV. → On these BEV projections, identify anatomic landmarks. → Define the field borders based on these landmarks.

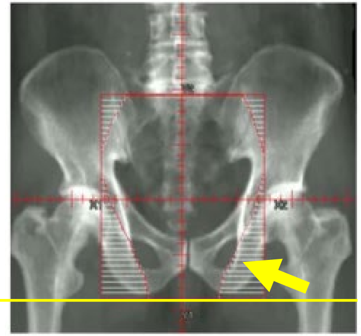
- Success rate when based on multiatlas contouring: 91%
- Version 2, with deep learning: 97%

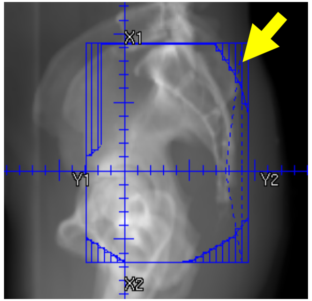
Kisling et al JGO 2019

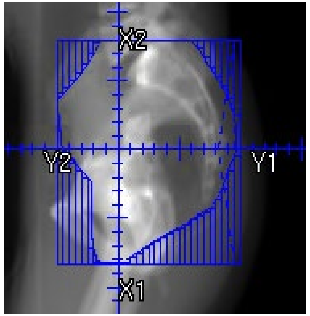
There are many different approaches to do the same thing











Research | Open Access | Published: 27 March 2019

Strategy to avoid local recurrence in patients with locally advanced rectal cancer

Takatoshi Nakamura, Takeo Sato, Kazushige Hayakawa, Wasaburou Koizumi, Yuji Kumagai & Masahiko Watanabe

Radiation Oncology **14**, Article number: 53 (2019) | Cite this article

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Dosimetric evaluation of Tomotherapy and four-box field conformal radiotherapy in locally advanced rectal cancer

Mina Yu, MD,[1] Hong Seok Jang, MS,[2] Dong Min Jeon, MS,[2] Geum Seong Cheon, BA,[2] Hyo Chun Lee, MD,[1] Mi Joo Chung, MD,[1] Sung Hwan Kim, MD,[1] and Jong Hoon Lee, MD[1]

MD Anderson Cancer Center:
- Inferior: bottom of foramen or 3cm inf GTV
- Posterior: 1cm post sacrum

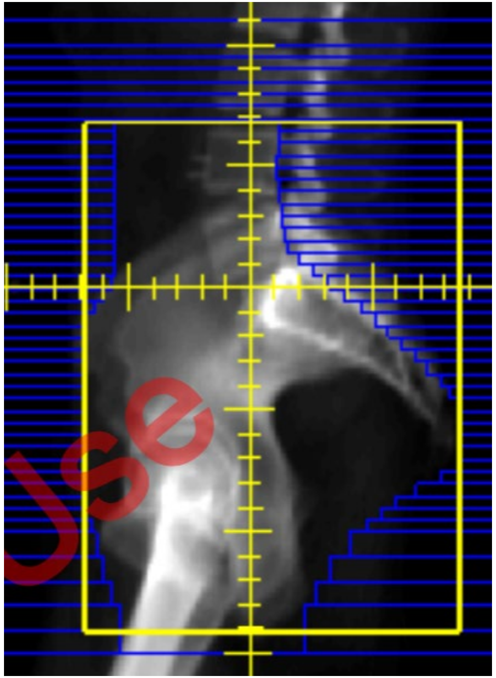
MD Anderson Cancer Center:
- Inferior: bottom of foramen or 3cm inf GTV and block AV
- Posterior: 1cm post sacrum

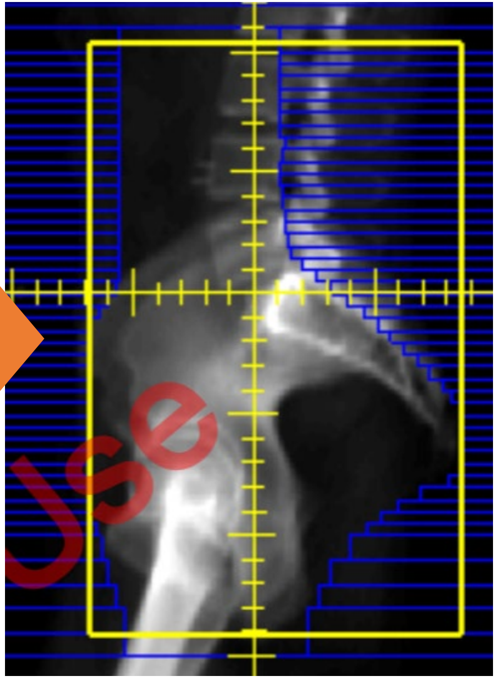
Centers in Japan & Korea:
- Inferior: bottom of ischium
- Posterior: do not go beyond the pelvic surface of sacrum

Kai Huang

So we need to accommodate different clinical practices

a) "standard" borders *OR* b) Add a reference point → "customized" borders

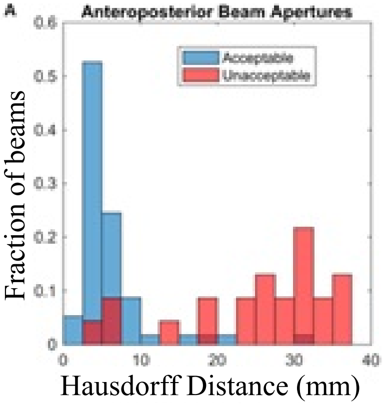


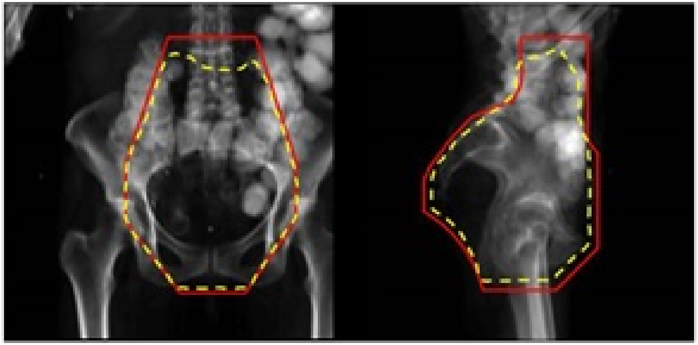


What about AI for quality assurance of the plan?

Primary and verification technique are acceptable

Primary technique is unacceptable

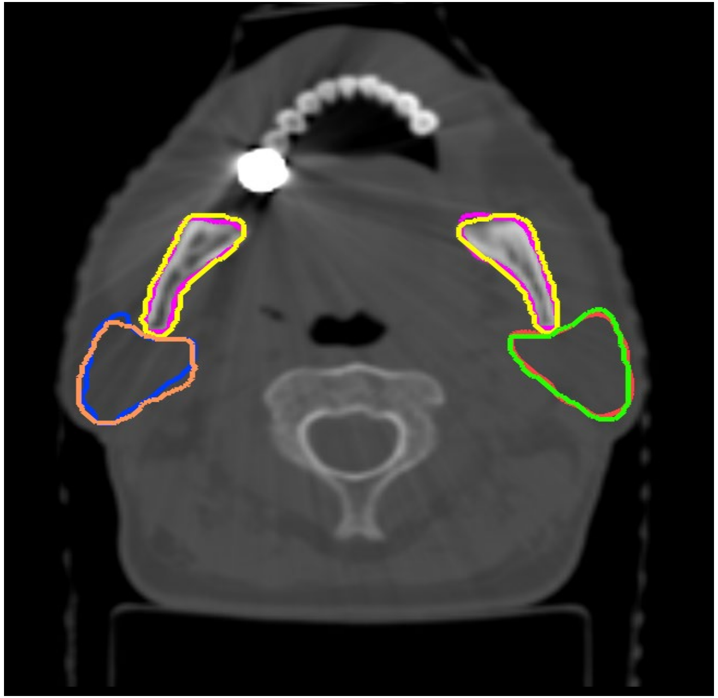


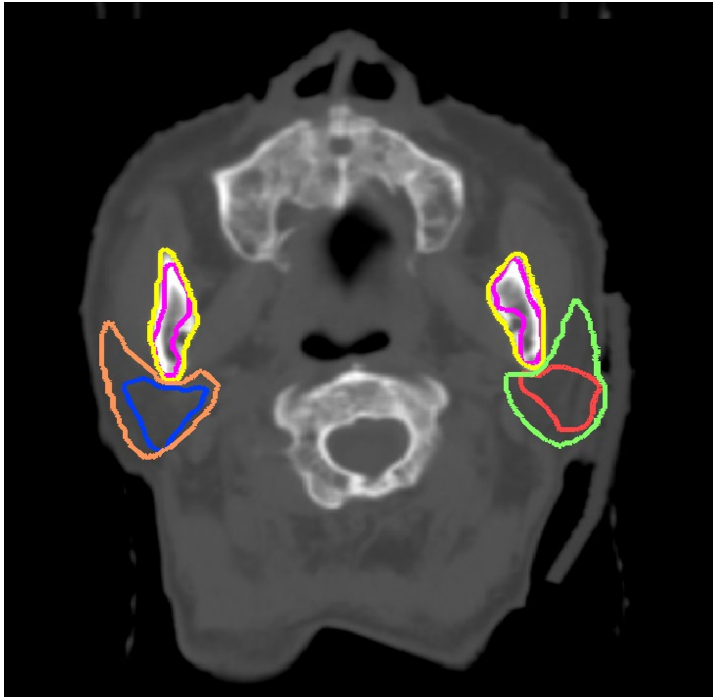


Verification technique is unacceptable

Kisling et al PRO 2020

We can apply the same idea to contour QA





- Effective at catching major errors (99%)
- Less effective at catching minor errors (80%)

Rhee et al Med. Phys. 2019

Radiation
Planning
Assistant

Possible contouring errors are flagged to the user

Brain	Value	Criteria	Status
MaxDist	3.5cm	< 1.1cm	!
Dice	0.97	> 0.97	!

BrainStem	Value	Criteria	Status
MaxDist	0.63cm	< 1cm	✓
Dice	0.87	> 0.82	✓

Cochlea_L	Value	Criteria	Status
MaxDist	0.76cm	< 0.7cm	!
Dice	0.25	> 0.57	!

Cochlea_R	Value	Criteria	Status
MaxDist	0.69cm	< 0.7cm	✓
Dice	0.38	> 0.57	!

Lens_L	Value	Criteria	Status
MaxDist	0.25cm	< 0.45cm	✓
Dice	0.58	> 0.55	✓

Lens_R	Value	Criteria	Status
MaxDist	0.28cm	< 0.45cm	✓
Dice	0.62	> 0.55	✓

Mandible	Value	Criteria	Status
MaxDist	2.5cm	< 1.1cm	!
Dice	0.89	> 0.83	✓

OpticNrv_L	Value	Criteria	Status
MaxDist	0.44cm	< 1.9cm	✓
Dice	0.53	> 0.55	!

OpticNrv_R	Value	Criteria	Status
MaxDist	0.35cm	< 1.9cm	✓
Dice	0.67	> 0.55	✓

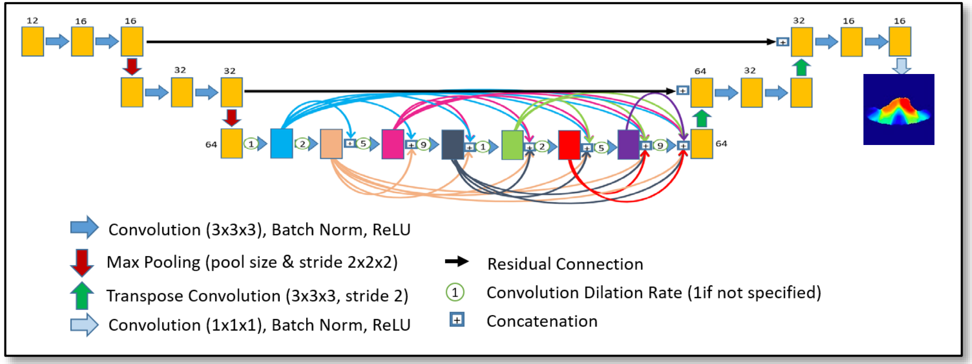
Eye_L	Value	Criteria	Status
MaxDist	0.79cm	< 0.6cm	!
Dice	0.89	> 0.88	✓

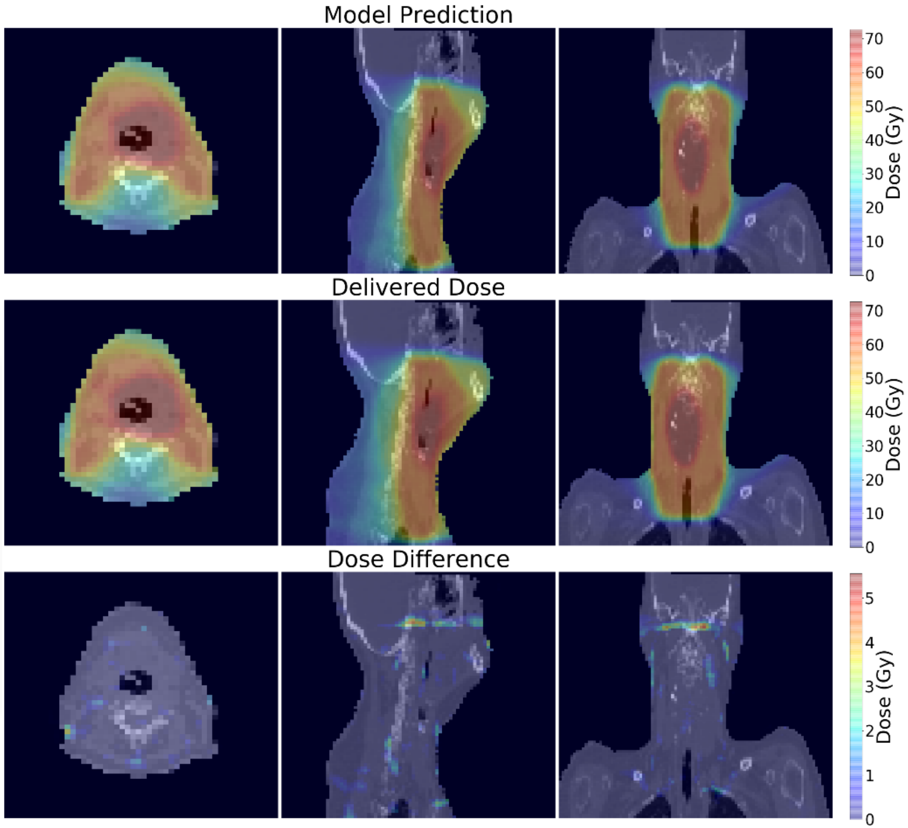
Eye_R	Value	Criteria	Status
MaxDist	0.79cm	< 0.6cm	!
Dice	0.92	> 0.88	✓

Parotid_L	Value	Criteria	Status
MaxDist	2cm	< 2cm	✓
Dice	0.81	> 0.73	✓

What about VMAT treatments?

- Densely-connected, Dilated U-Net (DDU-Net)
- 3D Inputs (12 channel)
  - CT
  - Body mask
  - Low-, medium-, and high-risk PTVs
  - OARs & normal structures

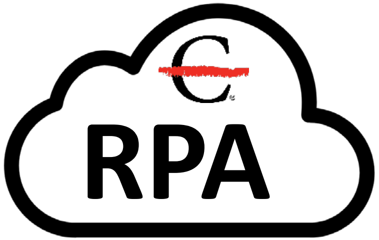




Based on: Zhang, J., Liu, S., Li, T., Mao, R., Du, C., & Liu, J. (2019). Voxel-Level Radiotherapy Dose Prediction Using Densely Connected Network with Dilated Convolutions. In D. Nguyen, L. Xing, & S. Jiang (Eds.), *Artificial Intelligence in Radiation Therapy* (pp. 70–77). Springer International Publishing

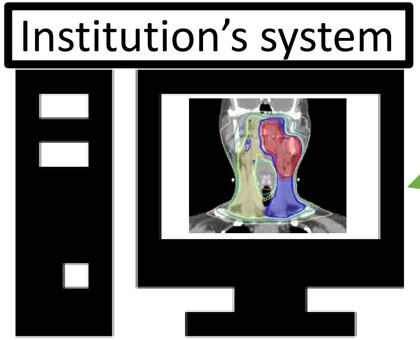
Gronberg, Gay, Netherton, Rhee, Cardenas
AAPM Grand Challenge 2020

Is automated treatment planning safe?

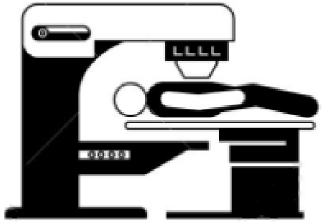


1. Upload CT and plan order

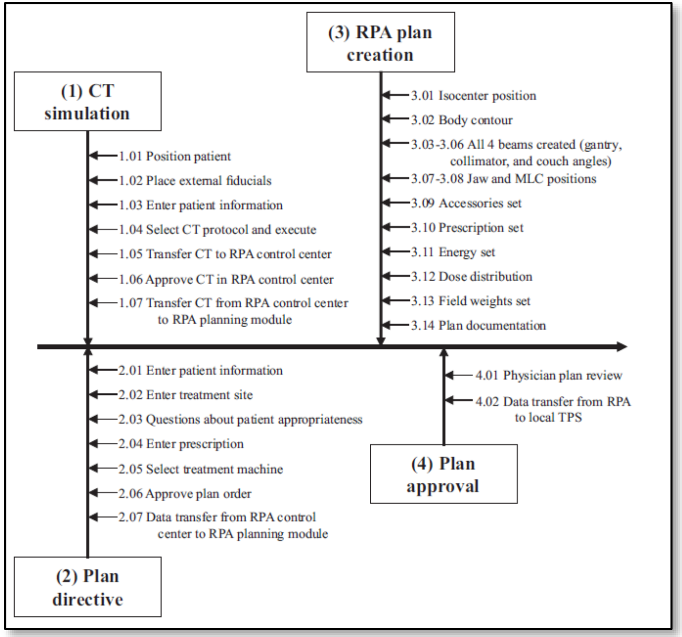
2. Download automatically generated contours, plan, QA



3. Edit contours, recalculate plan in local treatment planning system



4. After local QA, patient is treated

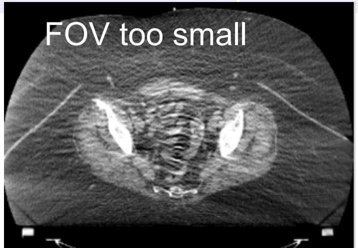


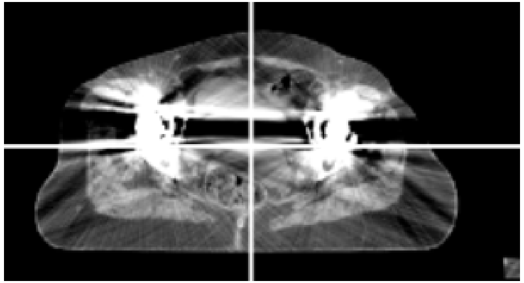
Kisling et al Med. Phys. 2019

Risk-assessment of AI-based planning

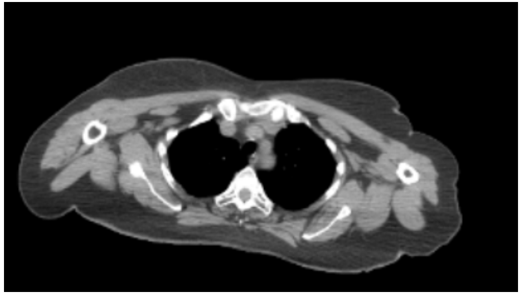
#	Major process	Step	Potential failure mode	Potential causes of failure	O	S	D	RPN
1	RPA plan creation	Isocenter position	Incorrectly identified	Other external fiducials used	7	9	5	315
2	Plan approval	Physician plan review	No comprehensive review*	Human error	3	10	10	300
3	RPA plan creation	Jaw positions	Inappropriate position	Algorithm error	10	7	4	280
4	RPA plan creation	MLC positions	Inappropriate position	Algorithm error	10	7	4	280
5	Plan directive	Enter prescription	Incorrect (not changed from default)	Human error	4	9	7	252
6	CT simulation	Select CT protocol and execute	Field-of-view is too small	Human error	5	8	6	240
7	CT simulation	Select CT protocol and execute	Field-of-view is too small	Patient is too large	5	8	6	240
8	Plan directive	Questions about patient appropriateness	Completed incorrectly	Human error	4	9	5	180

Kisling et al Med. Phys. 2019

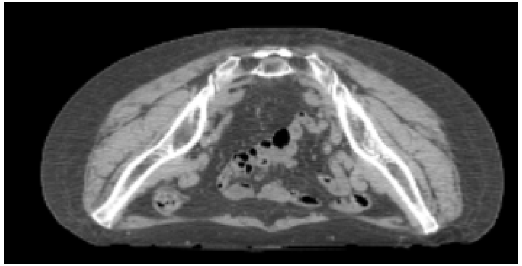




Artifacts



Not a cervix



Prone cervix

How do we safely deploy automated planning?

1. Training. Training should educate the end-users of automated planning about the potential sources of error, the impact of these errors on the patient, and that careful manual review of the plans to prevent these errors is essential.

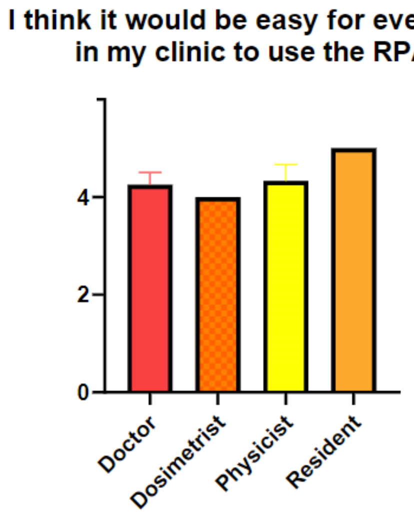
2. Automated QA. It is important to not only automate the planning, but to also include automated QA steps, as these can substantially the risk of automated planning.

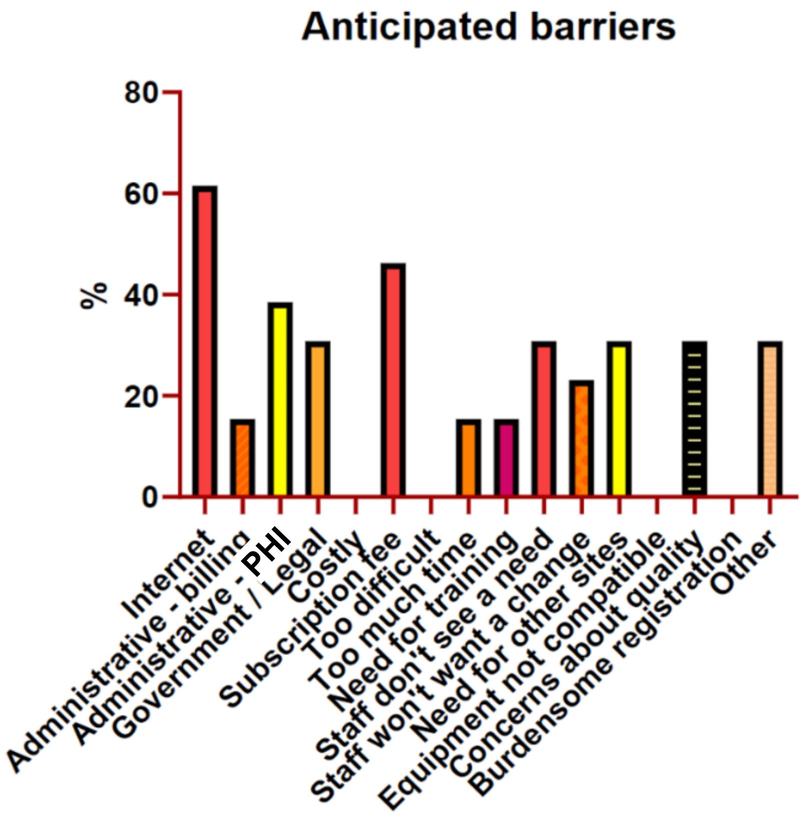
3. Manual plan checks. Physician review of the plans (and contours, where necessary) and physics checks are essential components of automated treatment planning.

Kisling et al Med. Phys. 2019

What are the hurdles to AI-based planning?

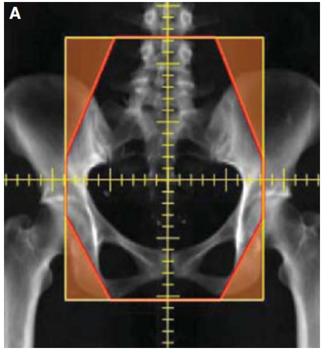
- 3 hospitals in South Africa
- 14 participants (radiation oncologists, physicists, and treatment planners)
- 1-hour usability session: 10min training video, then completed all tasks to run 3 plans (cervix, chest wall, head/neck)



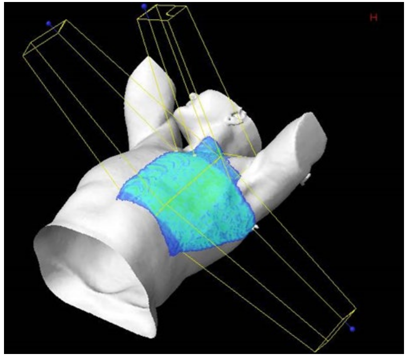


Wendy McGinnis

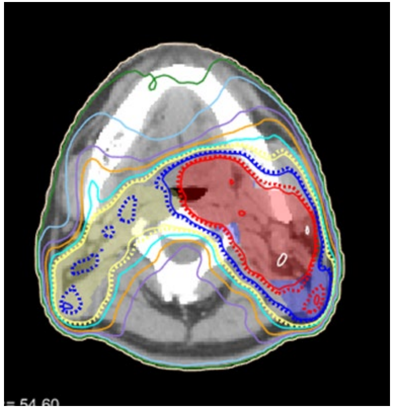
We can expect AI to touch all aspects of radiotherapy planning and QA



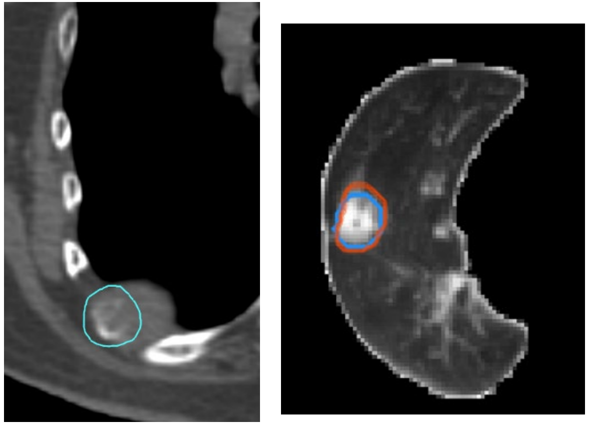
Simple Cervix



Chest wall

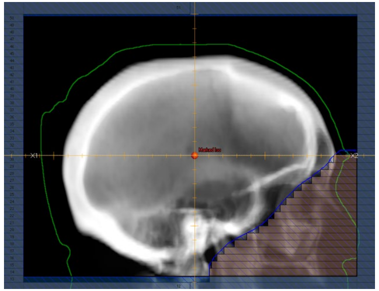


Head and Neck

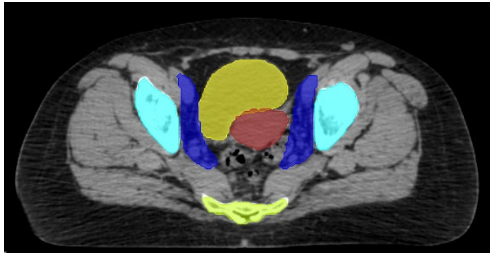


Target contouring

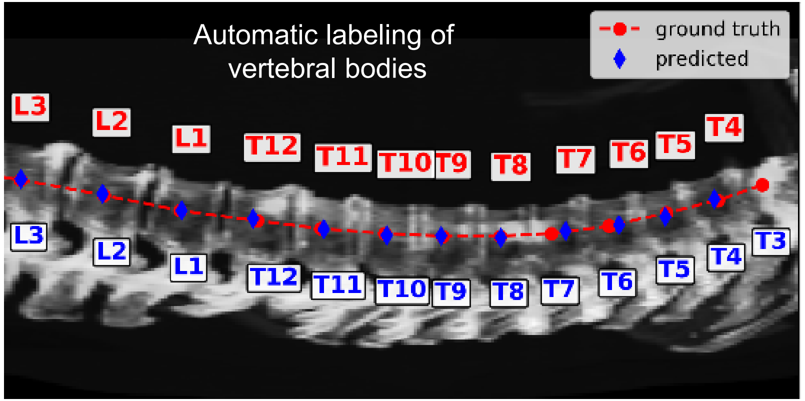
RPA



Whole brain



Complex cervix



Summary

AI is soon to touch all aspects of radiotherapy planning – contouring, planning and QA

Clinical deployment must remember that AI-planning isn’t perfect, and isn’t trained for all scenarios

Hurdles are mostly administrative, not related to quality

The future is bright, and we can expect AI to improve quality, efficiency, and fairness of radiotherapy

Acknowledgements

Thank you to our many partners at MD Anderson and beyond