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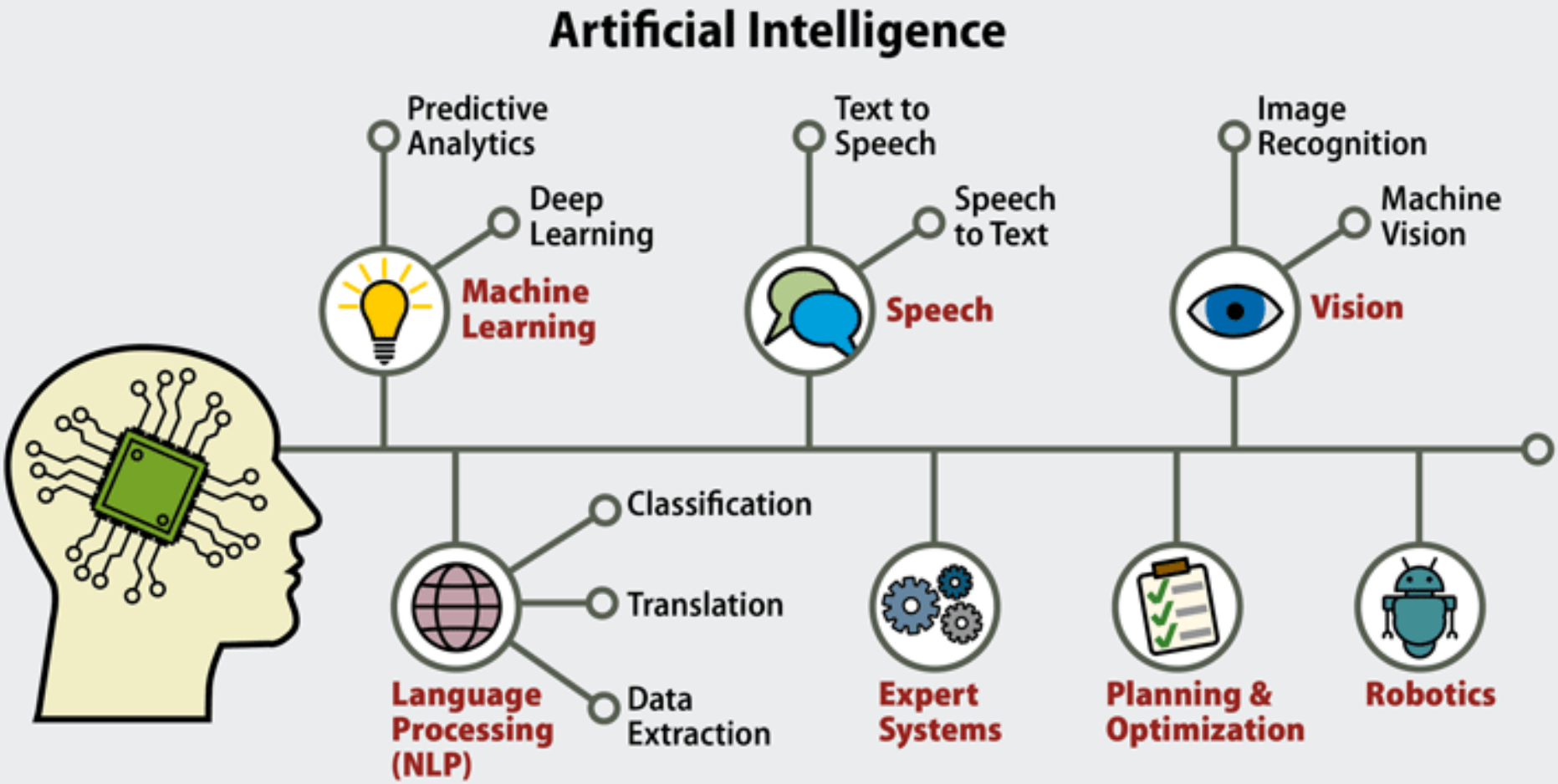
MEDICINOS FIZIKOS SKYRIUS

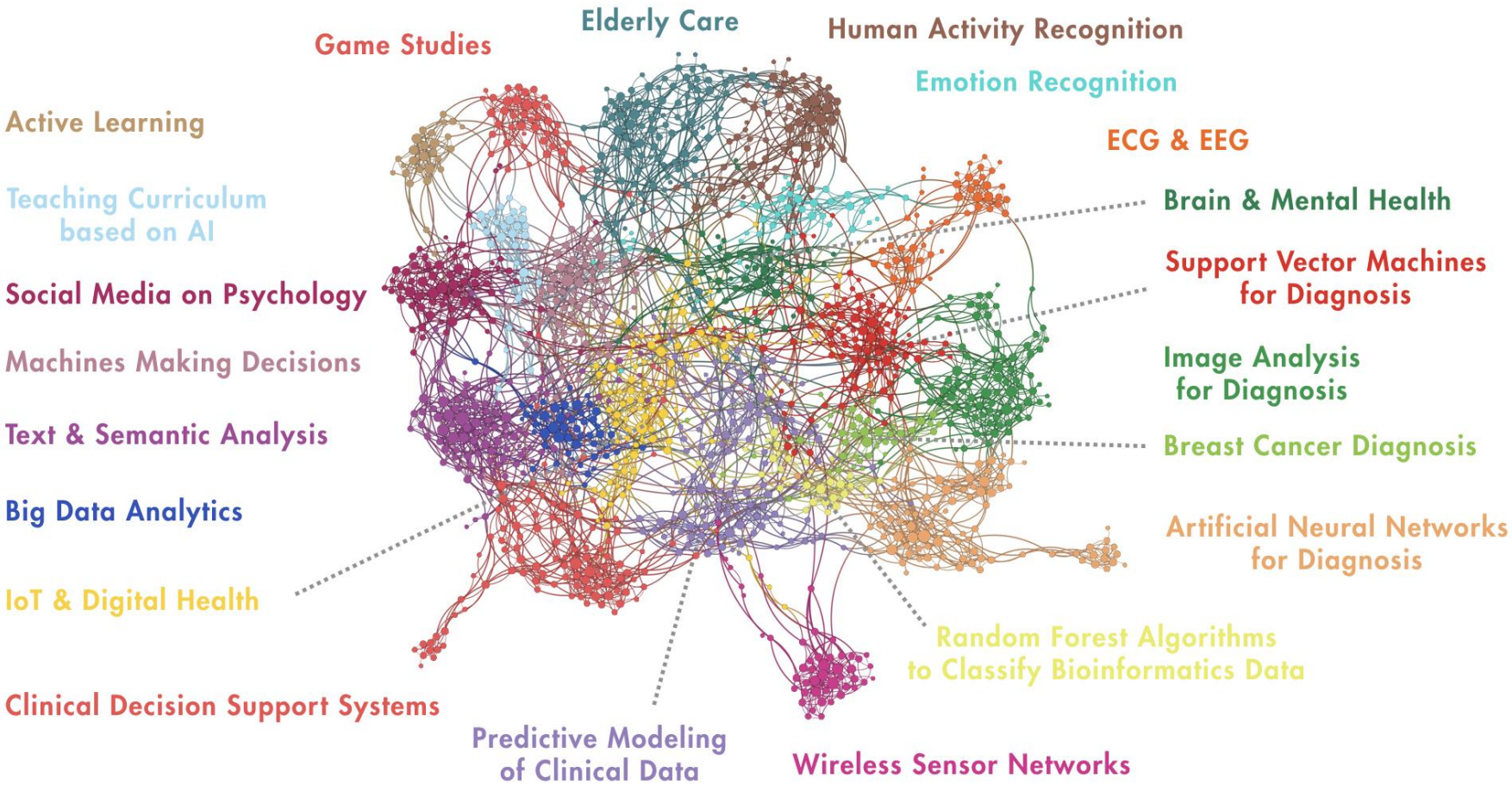
BENEFITS OF USING AUTOMATED ARTIFICIAL INTELLIGENCE OPTIMIZATION ALGORITHM IN RADIATION THERAPY

Romualdas Griškevičius, Marijus Astrauskas, Kęstutis Akelaitis, Ieva Markevičienė, Jonas Venius



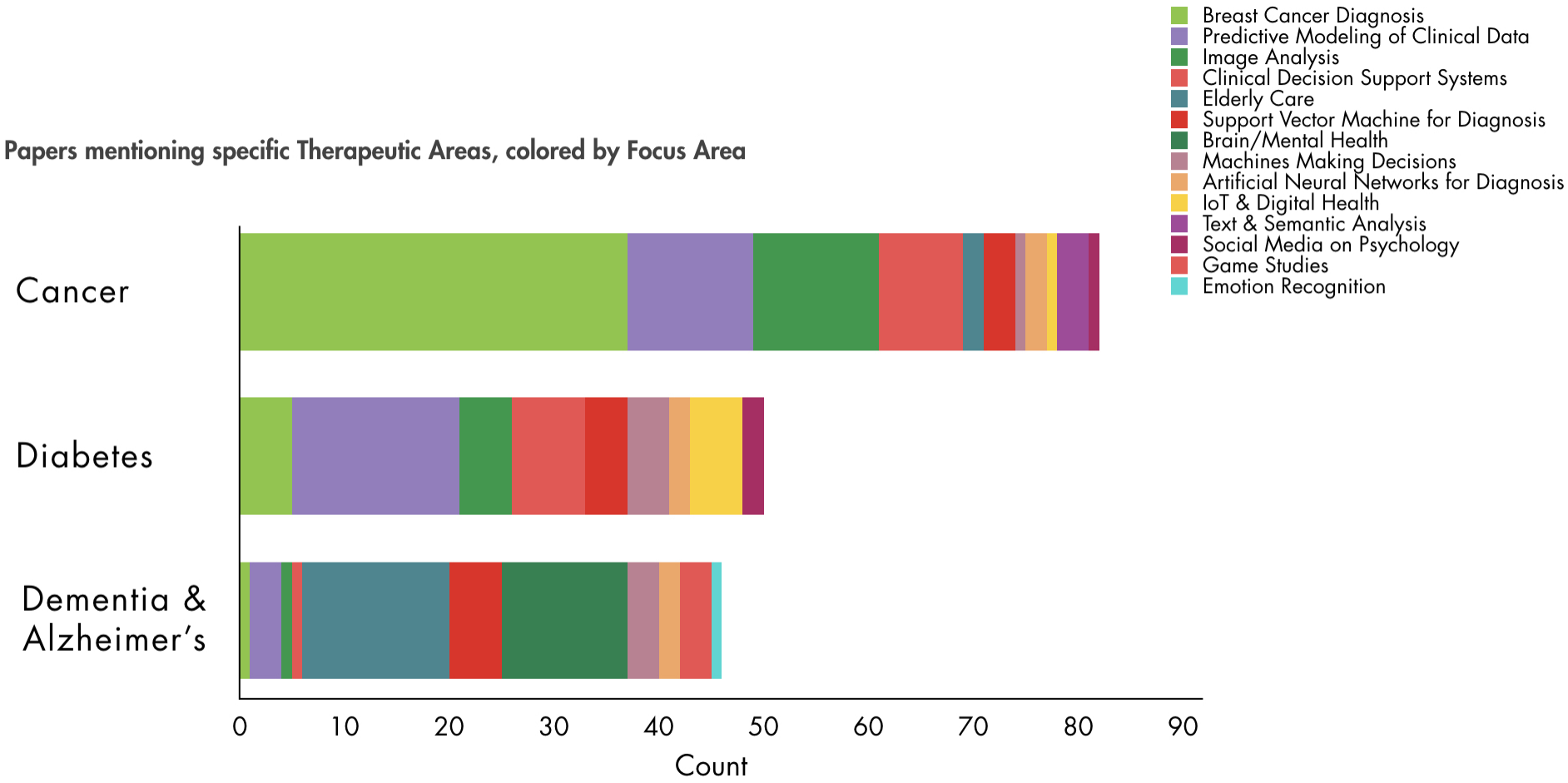
https://www.datamation.com/artificial-intelligence/what-is-artificial-intelligence.html

Academic papers on AI Healthcare 2016



https://quid.com/feed/paging-dr-robot-how-ai-will-transform-healthcare

AI focus areas



https://quid.com/feed/paging-dr-robot-how-ai-will-transform-healthcare

90+ Healthcare AI Startups To Watch

Imaging & Diagnostics

ablacon, aidence, aidoc, Healthy.io, PathAI, RadiomicsAI, Aillis, EXO, deepwise, 推想科技 infervision, sight, enlitic, freenome, JLK INSPECTION, zebra, BUTTERFLY Network, Inc., IBEX, IDx, SIGTUPLE, ULTROMICS, vuno, VoxelCloud, Lunit, viz, PAIGE

Drug Discovery

Accutar Biotech, BenevolentAI, DIP, FINCH THERAPEUTICS, APEIRON, BlackThorn THERAPEUTICS, Frontier MEDICINES, insitro, Atomwise, Exscientia, engine, JUVENESCENCE, Notable Labs, OWKIN, RECURSION, 药研社, Standigm, XtalPi, twoXAR, SPRING DISCOVERY

Predictive Analytics & Risk Scoring

BenchSci, lu, 森亿智能 SYNYI·AI, saama, GNS HEALTHCARE, Medial EarlySign, TEMPUS, ikioo, medopad, Welltok, nference

Genomics

DECIPHER BIOSCIENCES, SOPHIA GENETICS, Syntekabio, WuXiNextCODE

Fitness

FINC, Vi

Virtual Assistant

babylon, Curai, mfine, notable, buoy, K, Suki

Hospital Decision Support

binaryfountain, Cardinal Analytx, Qventus, gauss, Olive, OM1, KenSci, NextHealth TECHNOLOGIES, LeanTaaS, Medical INFORMATICS

Clinical Trials

deep, HEALTH[AI]SCALE TECHNOLOGIES, teckro.

Nutrition

NURITAS, WHOLE BIOME

Remote Monitoring

biofourmis, ContinUse Biometrics, DENTAL MONITORING

Compliance

DATAVANT, PROTENUS

Mental Health

mindstrong

Created by You. Powered by CBINSIGHTS

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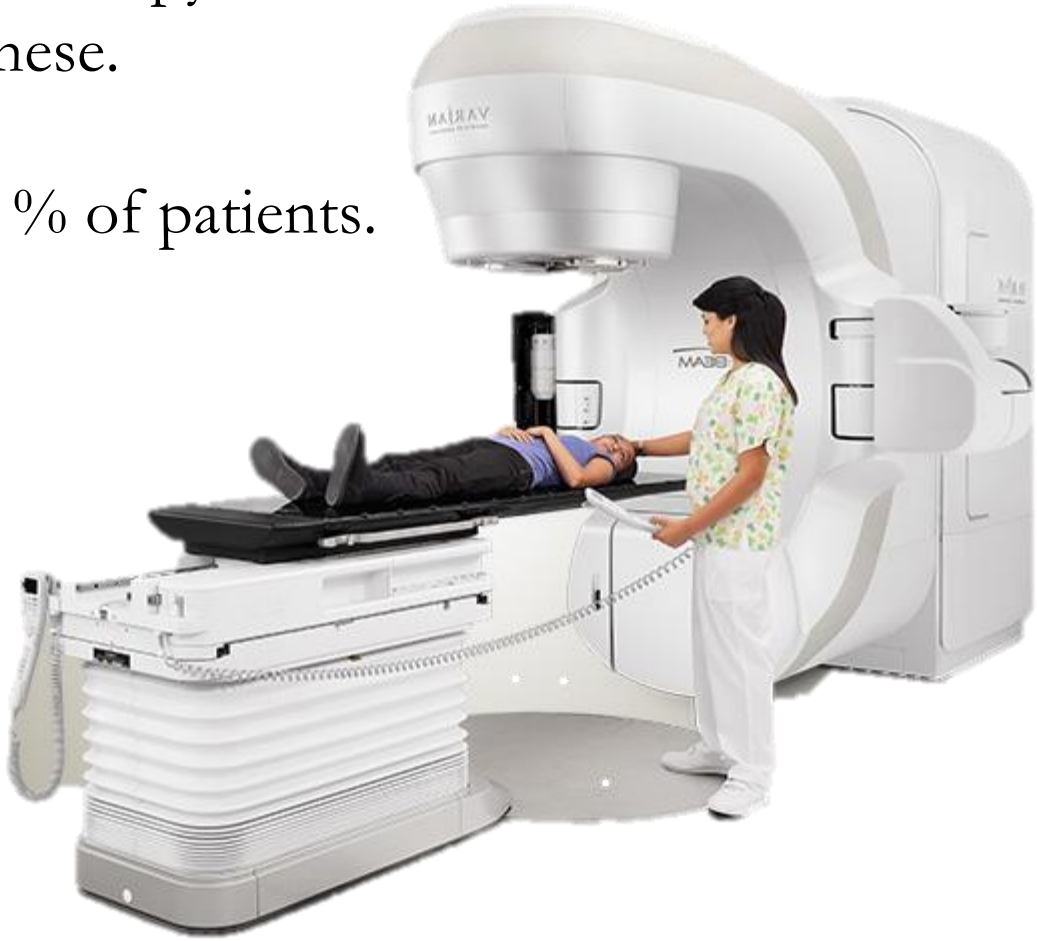
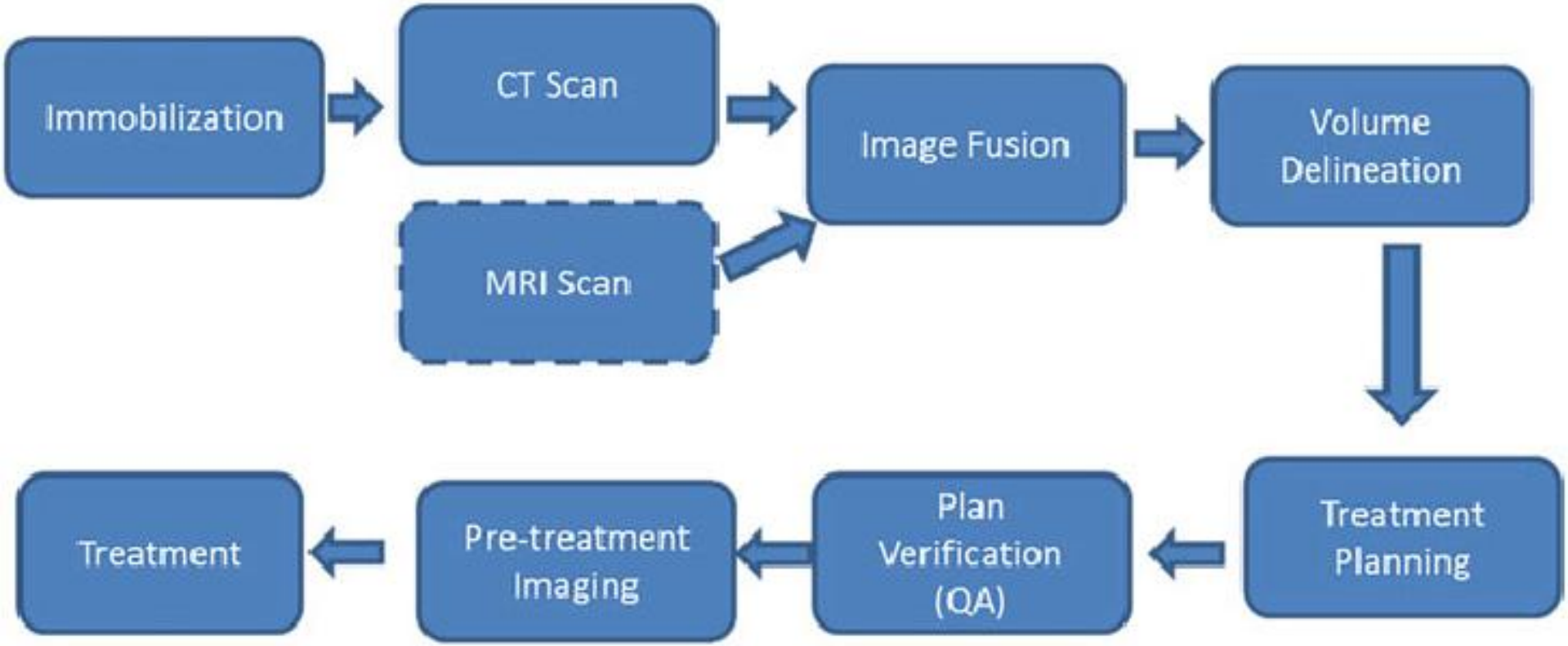
The main methods of treating cancer are surgery, radiation therapy (RT), chemotherapy and a combination of all these.

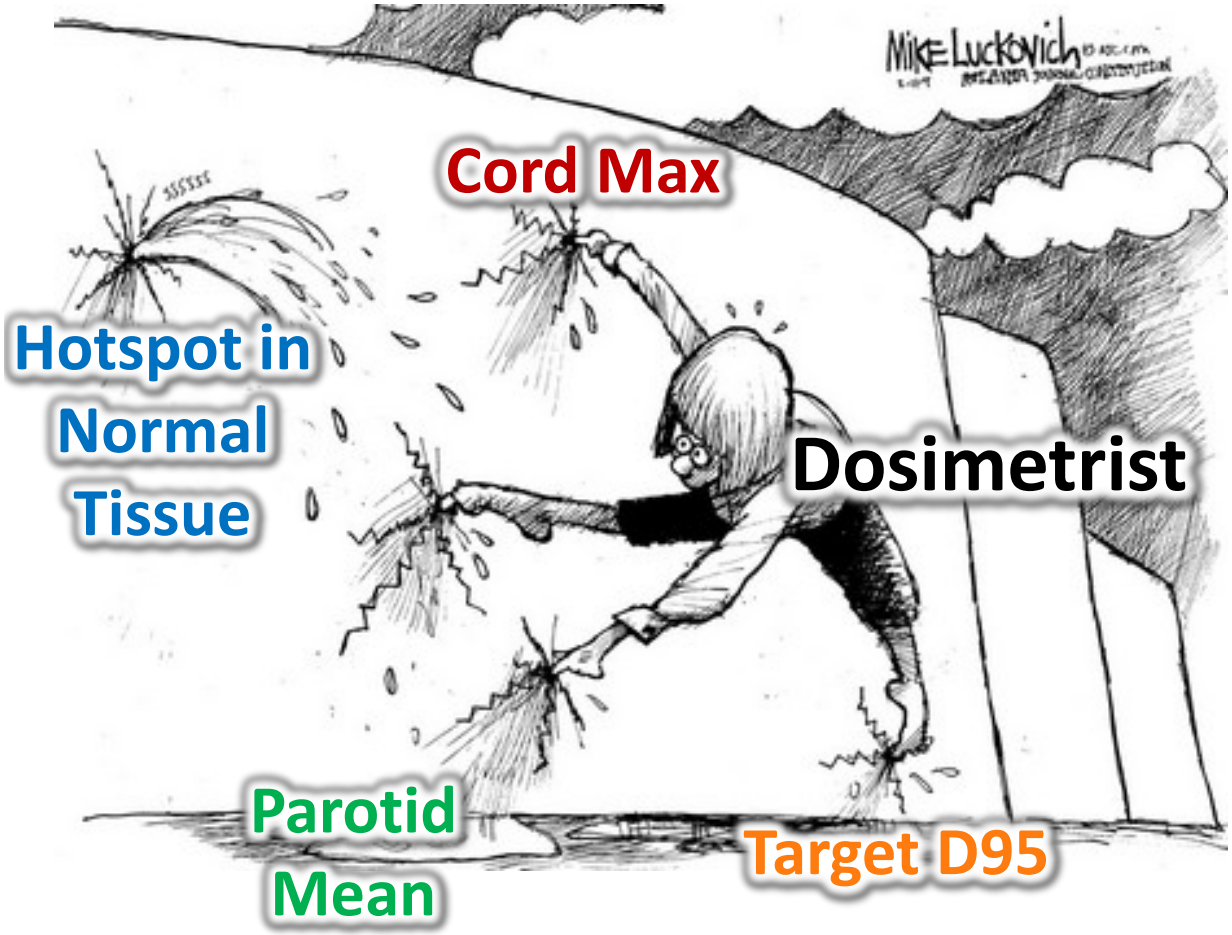
RT can be applied in up to 50 % of patients.



RT workflow


Immobilization
CT Scan
MRI Scan
Image Fusion
Volume Delineation
Treatment Planning
Plan Verification (QA)
Pre-treatment Imaging
Treatment

RT planning


Cord Max
Hotspot in Normal Tissue
Dosimetrist
Parotid Mean
Target D95

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RT planning

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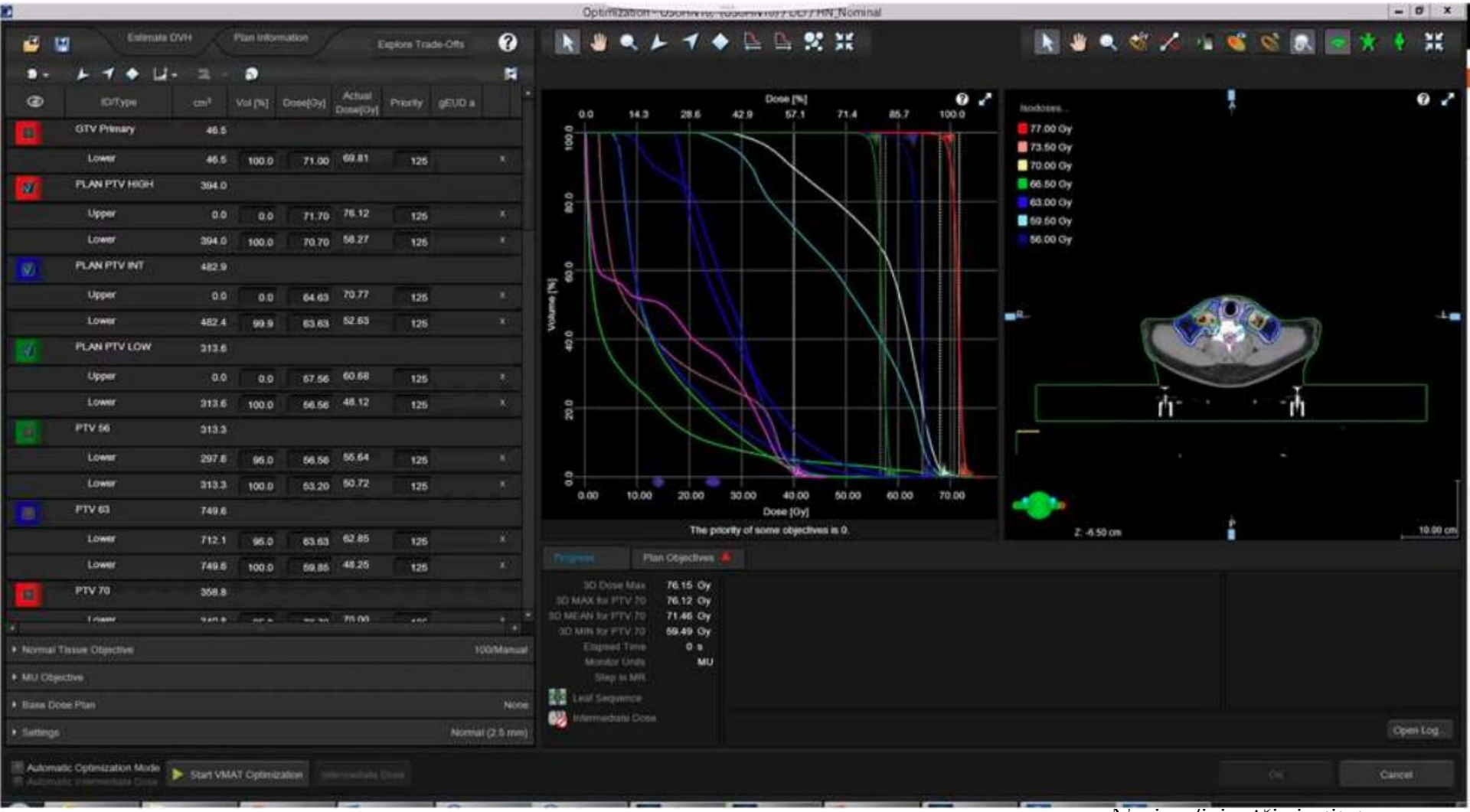
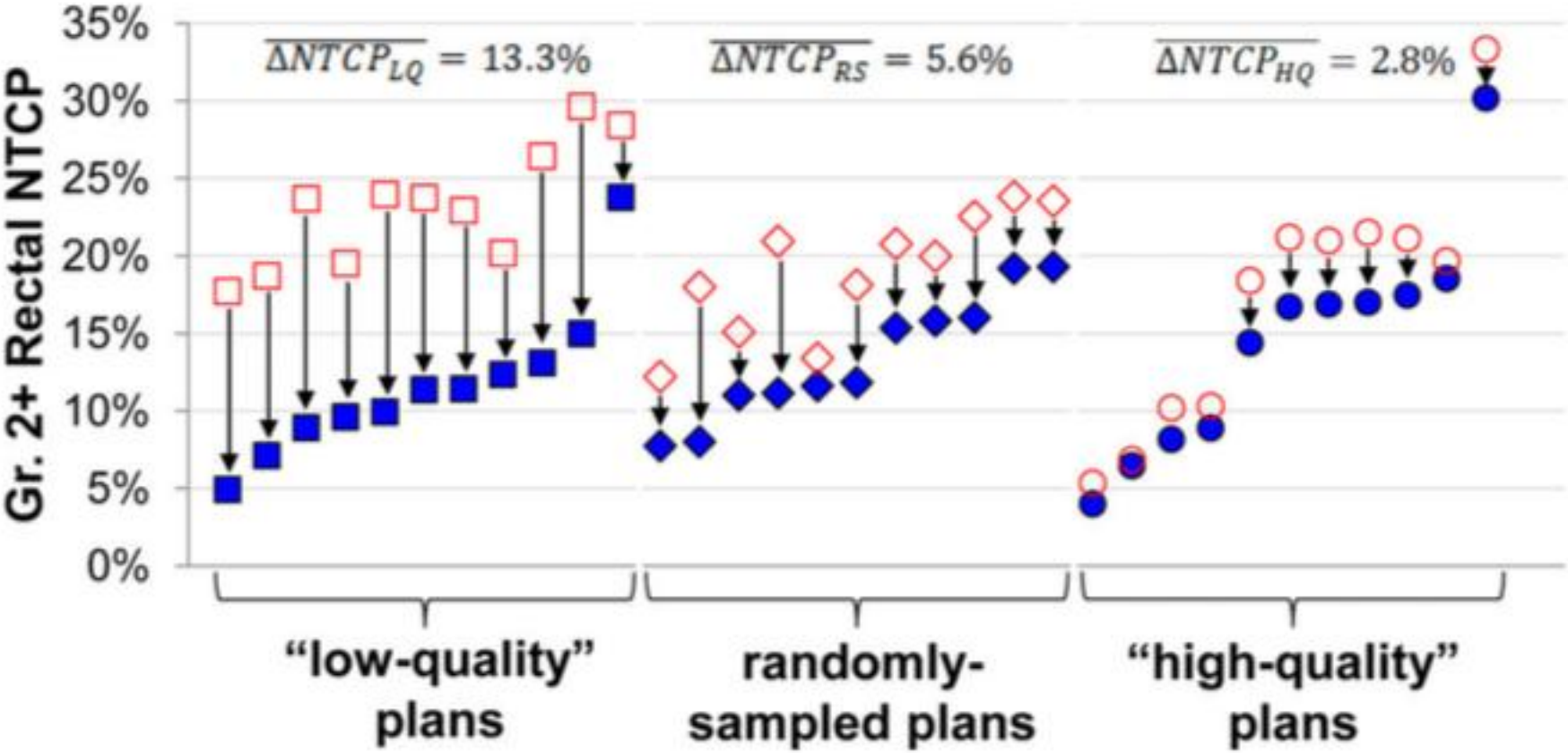


RT planning

Is created RT plan optimal?



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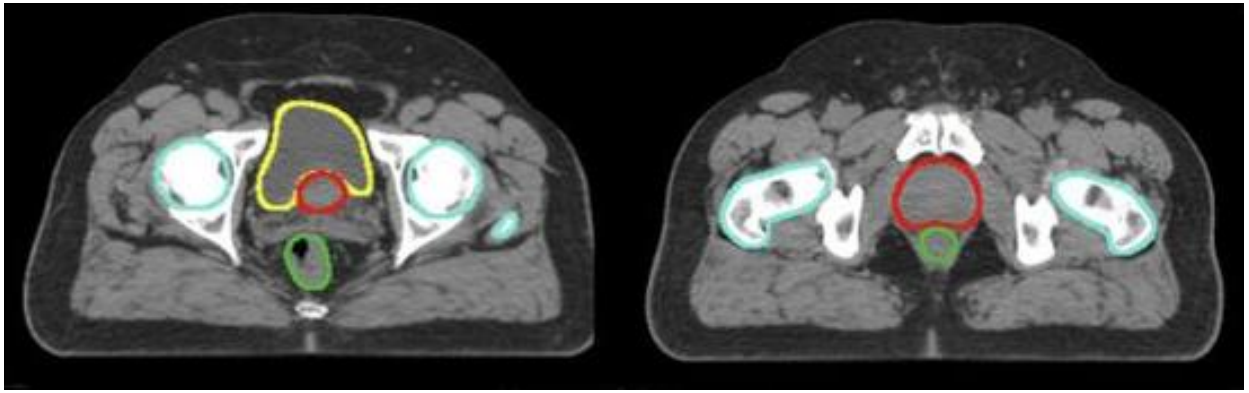
Quantifying unnecessary normal tissue complication risks due to suboptimal planning: a secondary study on RTOG0126

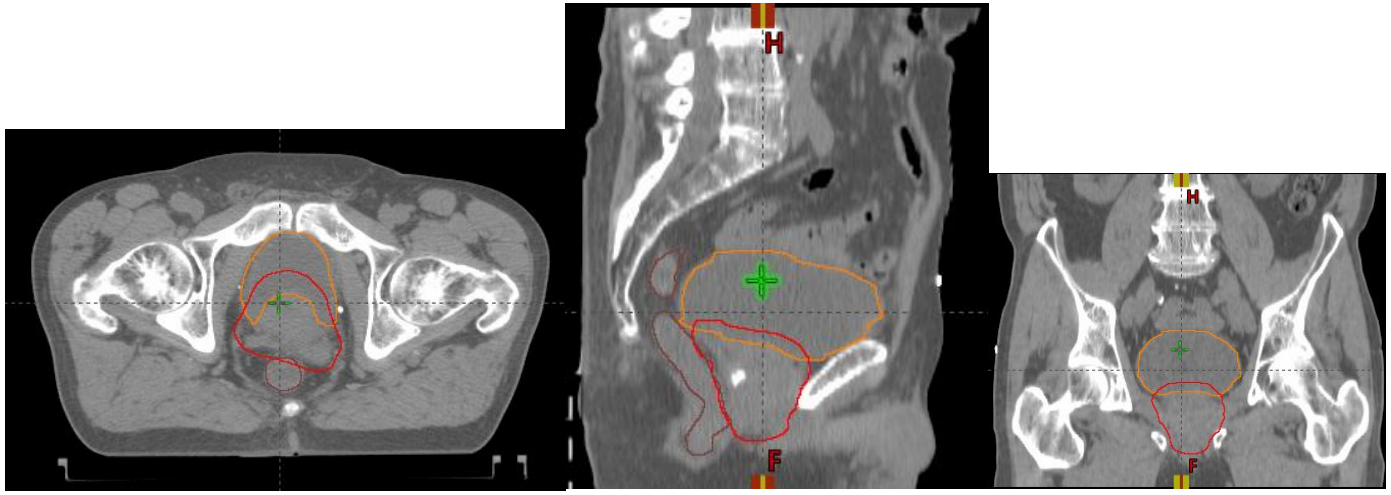
Kevin L. Moore, PhD[1], **Rachel Schmidt**[2], **Vitali Moiseenko, PhD**[1], **Lindsey A. Olsen, MS**[3], **Jun Tan, PhD**[3], **Ying Xiao, PhD**[4], **James Galvin, PhD**[4], **Stephanie Pugh, PhD**[5], **Michael J. Seider, PhD, MD**[6], **Adam P. Dicker, MD**[4], **Walter Bosch, DSc**[3], **Jeff Michalski, MD**[3], and **Sasa Mutic, PhD**[3]

- Our aim was:
  - evaluate the quality of the plans created by RapidPlan models.
  - Measure RapidPlan plans preparation time.
  - Evaluate complexity of RapidPlan plans.

Methodology

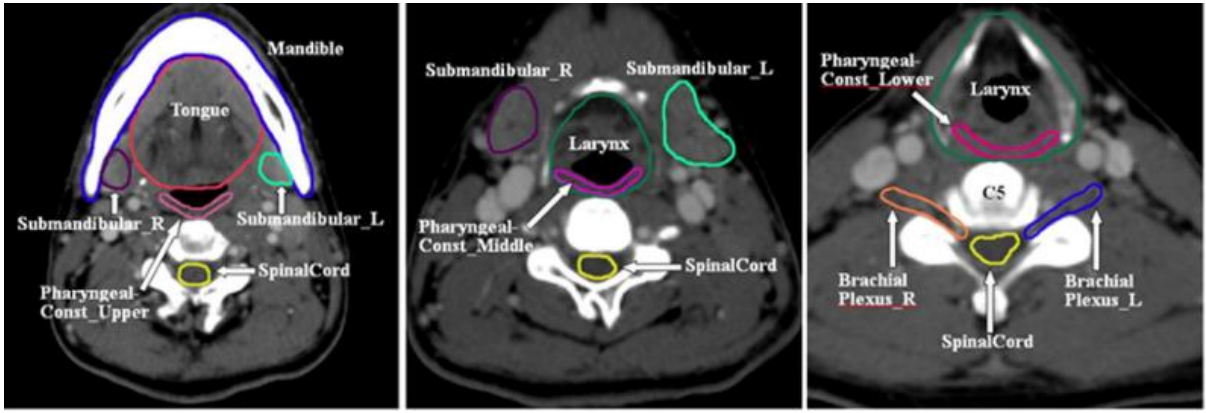
- Simple case – Prostate cancer:
  - One target
  - OAR's :
    - Bladder
    - Rectum

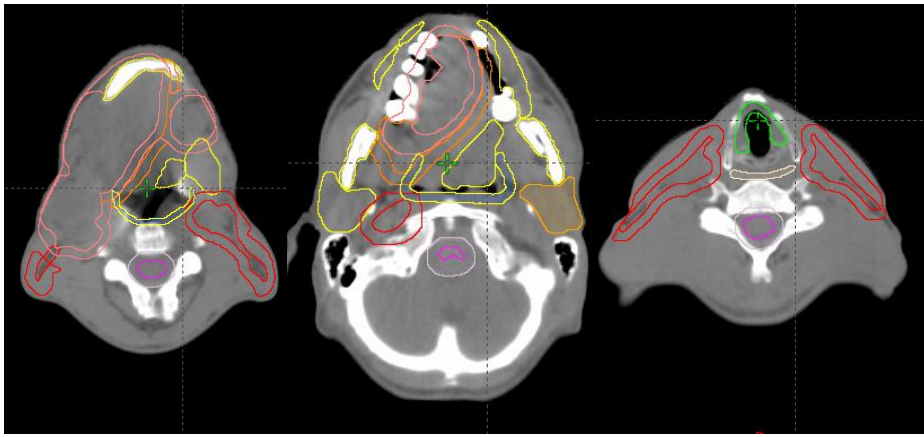




Methodology

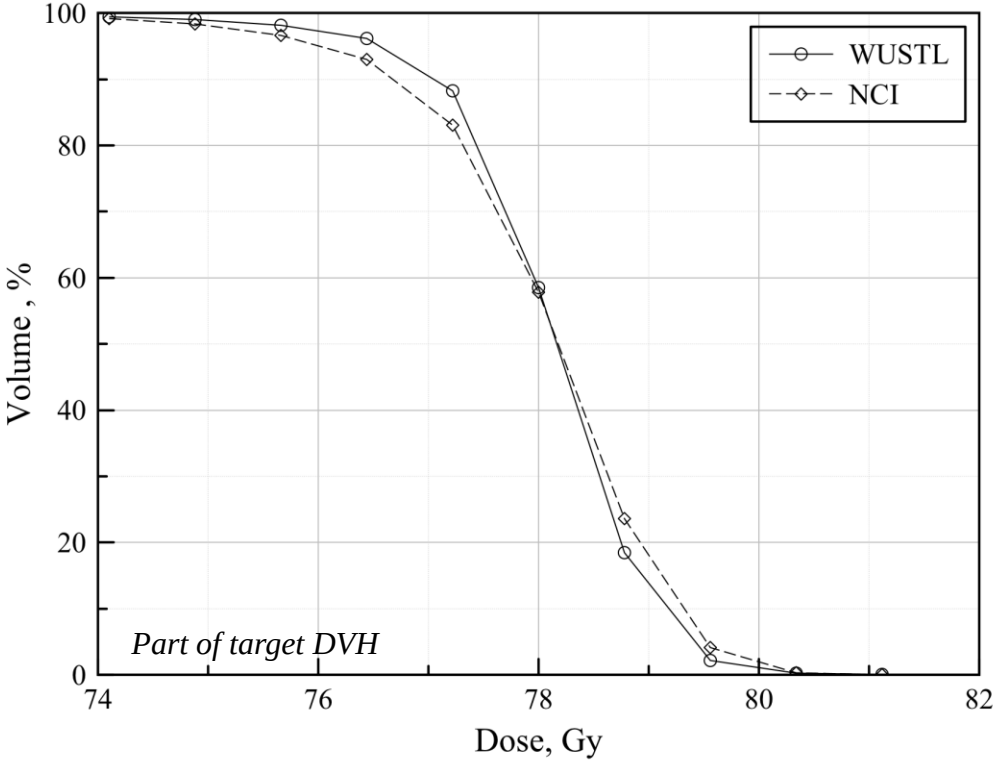
- Complicated case – Head&Neck cancer :
  - Three targets
  - OAR's :
    - spinal cord,
    - parotid glands,
    - oral cavity,
    - mandibular,
    - larynx,
    - esophagus,
    - pharyngeal constrictor muscles





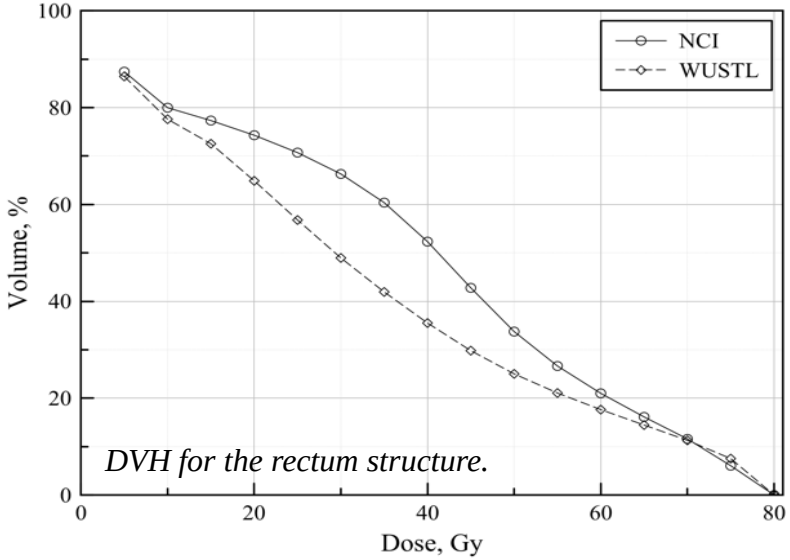
Results – Prostate case

- WUSLT algorithm improved (by little) the quality of the plan.
- There was a slight increase in homogeneity index, conformal index, D5% and D95%.

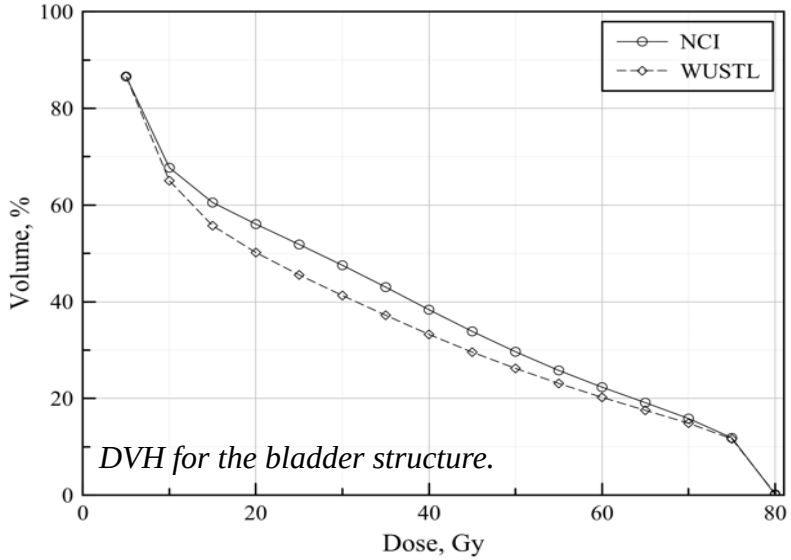


Results – Prostate case

- WUSLT algorithm achieved significant differences in rectal and bladder DVHs.
- The mean dose to rectum structure was 5.72 Gy lower in WUSTL model (33.12Gy in WUSTL vs. 38.84Gy in NCI plans).
- The mean dose to bladder structure was 2.55 Gy lower in WUSTL model (30.5 Gy in WUSTL vs 33.05 Gy in NCI plans).



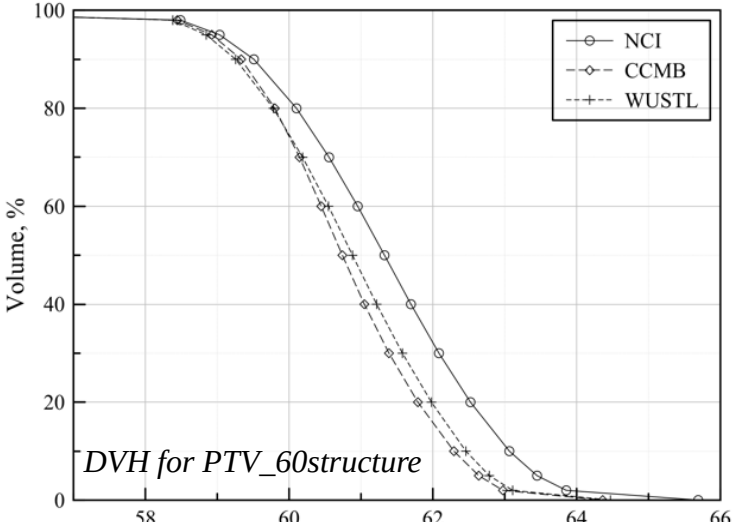
DVH for the rectum structure.

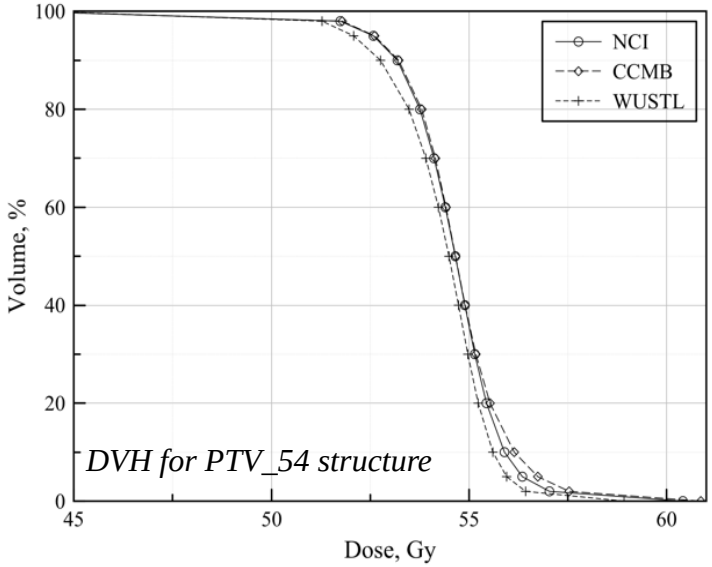


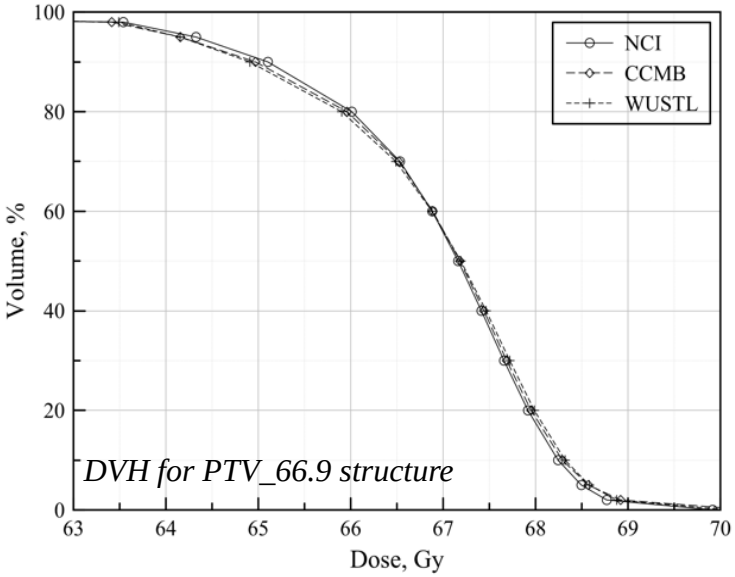
DVH for the bladder structure.

Results – H&N case

- RP models performed better on medium dose target (PTV_60), slight improvements were observed in D5%, D95%, also on DHI, and CI metrics.
- For the low dose target (PTV_54) CCMB coverage was the same as NCI, but WUSTL coverage was poorer.
- No difference was observed in high dose target (PTV_66.9).

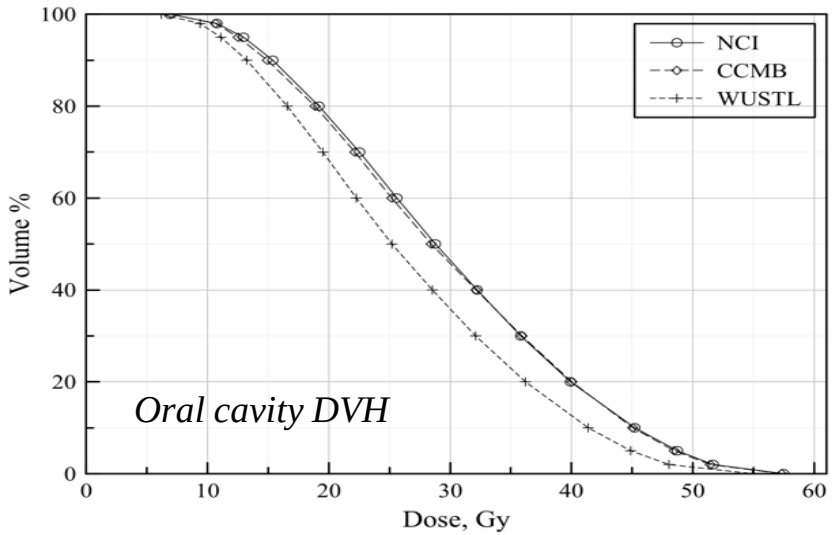


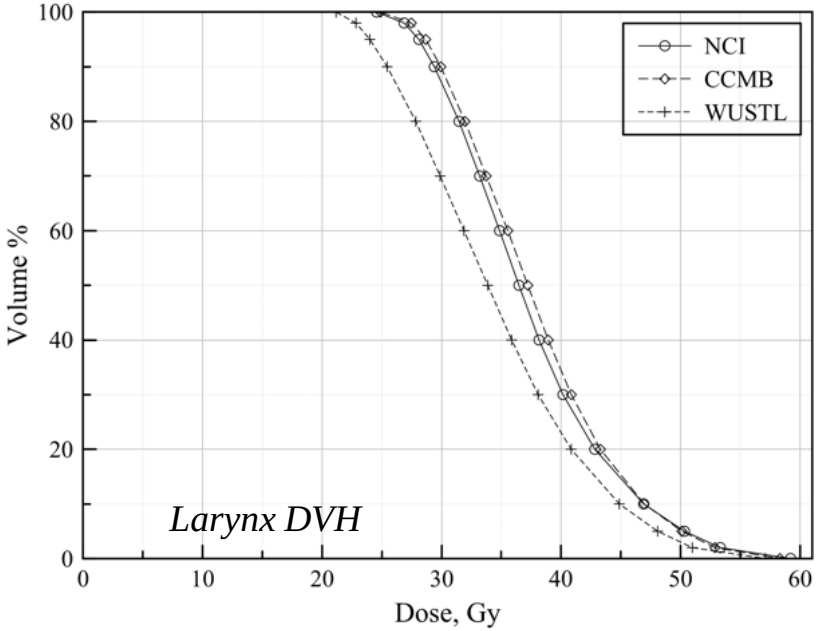


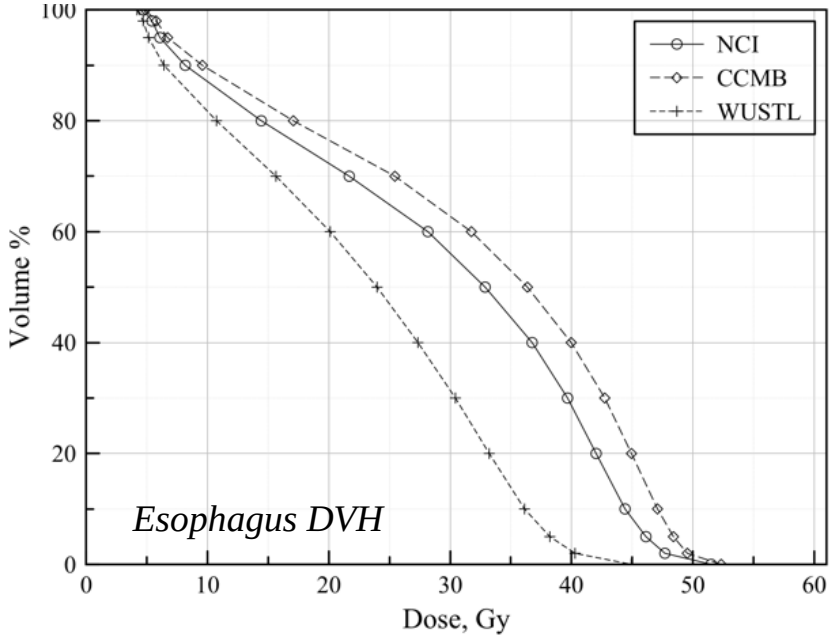


Results – H&N case

- Oral cavity structure WUSLT algorithm did better than NCI, lowering mean dose by 3Gy (WUSTL 26,38Gy vs. NCI - 29,60Gy).
- Esophagus mean dose was smaller in WUSTL created plans (WUSTL 22.66Gy vs. NCI 29.47Gy).
- Larynx mean dose was smaller in WUSTL model plans (WUSTL 34.56Gy vs. NCI 37.37Gy).







Plan creation time

- "Simple case" – Prostate cancer:
  - RP methodology on average it took 2.7 minutes
  - Manual optimization - 40-90 minutes.

- "Complicated case" – Head&Neck cancer:
  - RP methodology it took on average 4.3 minutes;
  - Manual optimization – 60-100 minutes.

Plan “complexity”

- On average, prostate RP plans had 111.2 MU more than conventional plans (NCI plan 570.3, RP plan 681.5).
- RP plans for H&N cases had 57 MU less than NCI plans (NCI plan 584,8, CCMB plan 523,8, WUSTL plans 532,3).

Results – Summary

Metric	NCI	CCMB	WUSTL
Oral cavity			
DMEAN	29,60	29,38 p=0,67	26,38 p<0.001
Esophagus			
DMEAN	29.47	32.25 p=0,0008	22.66 p<0.001
Larynx			
DMEAN	37,37	37,87 p=0,68	34,56 p=0,08
Spinal cord			
DMAX (Gy)	36,4	40.29 p<0.001	38.82 p=0.0001
Mandibulla			
DMAX	61,35	62,16 p=0,008	61,53 p=0,66
Parotis sin			
DMEAN	27,06	26,22 p=0,17	29,69 p=0,0004
Parotis dex			
DMEAN	25,02	25,38 p=0,25	28,60 p=0,000006
Inferior pharyngeal constrictor muscle			
DMEAN	43,98	43,80 p=0,86	43,11 p=0,49
Superior pharyngeal constrictor muscle			
DMEAN	45,61	46,13 p=0,34	45,38 p=0.71
Middle pharyngeal constrictor muscle			
DMEAN	45.67	46,07 p=0,71	47,37 p=0,21

Metric	NCI_54	CCMB_54	WUSTL_54
DHI	0.10	0,11 p=0,045	0,09 p=0,54
CI	1.25	1.19 p=0.007	1.3 p=0.02
D95%	52.58Gy	52.61 p=0,73	52.08 p=0,00001
D5%	56.34Gy	56.74 p=0,007	55.60 p= 0,005
	NCI_60	**CCMB_60**	**WUSTL_60**
DHI	0,09	0.07 p=0,0015	0,08 p= 0,006
CI	0.89	0.88 p=0.6	0.94 p=0.0004
D95%	59.03	58.92 p=0,2208	58.85 p=0,0465
D5%	63.45	62.64 p=0,0002	62.79 p=0,0014
	NCI_66.9	**CCMB_66.9**	**WUSTL_66.9**
DHI	0,08	0,08 p=0,22	0,08 p=0,47
CI	1.04	0.87 p=0,02	1,22 p=0.000005
D95%	64,33	64.16 p=0,2	64.15 p=0,14
D5%	68.50	68.57 p= 0,39	68.58 p=0,3

Results –Summary

Metric	NCI	WUSTL
	Rectum	
DMEAN	38.84	33.12 p<0.001
	Bladder	
DMEAN	33.05	30.5 p<0.001
	Prostate	
DHI	0.06	0.05 p=0.047
CI	0.59	0.60 p=0.519
D95%	76.2	76.7 p=0.018
D5%	79.4	79.2 p=0.036

Metric	NCI	RP models
	Plan time	
Plan time (Prostate)	40	2.7
Plan time (H&N)	60	4.3
	Complexity	
MU (Prostate)	570.3	681.5
MU (H&N)	584.8	528.05

Conclusions

1. For simple cases AI finds slightly better solutions.
2. For complex cases AI benefits are more debatable.
3. All plans generated by both RP algorithms were acceptable for treatment and were optimized in significantly shorter time.