Automation in Radiotherapy Planning: current Approaches and Future Perspectives

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ICTP/School on Medical Physics for Radiation Therapy: Dosimetry, Treatment Planning and Delivery for Advanced Applications
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Modern Radiotherapy Approaches

- **IMRT** - Intensity modulated radio therapy
- **IGRT** - Image-guided radiotherapy
- **SGRT** - Surface-guided radiotherapy
- **ART** - Adaptive radiotherapy
- **oART** - Online Adaptive Radiotherapy
- Stratified or personalized radiotherapy.

of all these methods → High-quality & efficient treatment planning

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Is Plan Quality Crucial?

Randomized trials of combined modality Treatment

- Each modality assumed correctly delivered **or**
- Incorrect RT delivery may be wash out by randomization
- Absolute outcomes ↓, but comparative efficacy between regimens remains valid

Tirapazamine + Cisplatin in HNSCC Trial

- 861 patients, 82 centers, 16 countries
- **RT:** 70 Gy / 35 fractions / 7 weeks (both arms)
- **CT:** dose calculation & GTV coverage verification
- **Techniques:** 2 opposing fields / 3D conformal / ~~IMRT~~ (2010)
- **Planning:** 2D (53%) vs. 3D (47%)

After treatment some non-compliant treatment plans discovered (dose coverage, delineation, treatment prolongation).
The deviation rate CIS (24.3%) and CIS/TPZ (26.5%).

https://doi.org/10.1200/JCO.2009.27.4498

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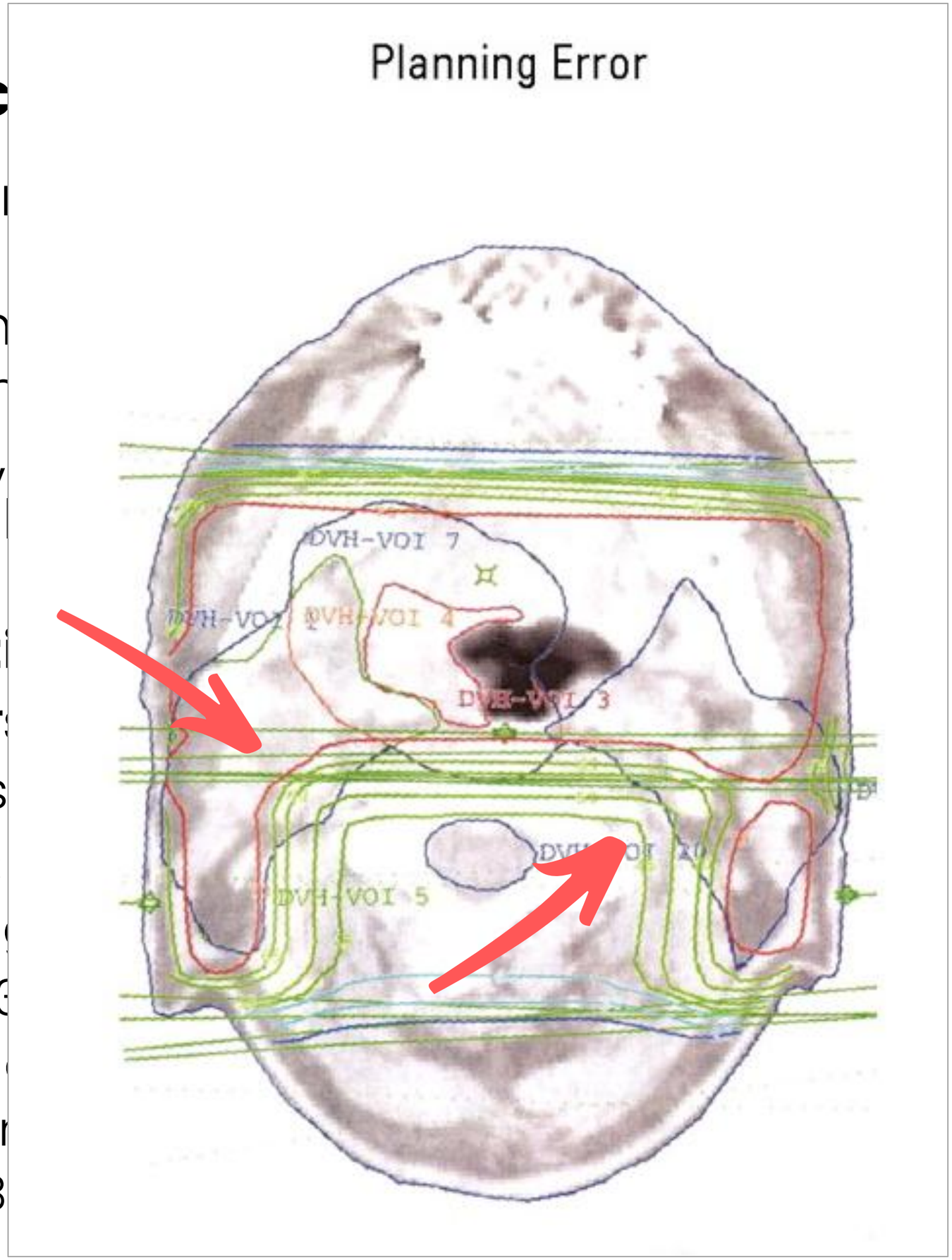
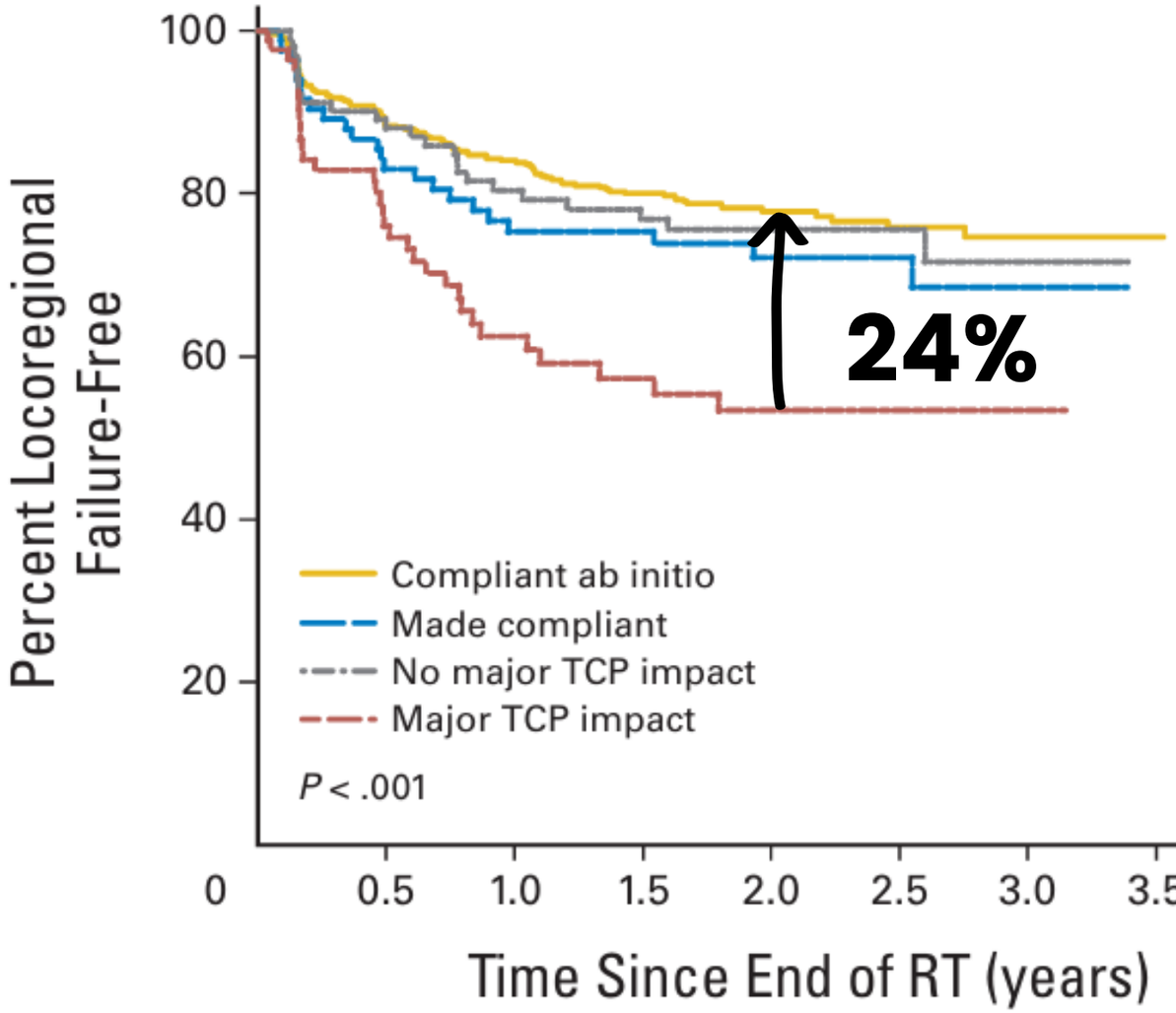
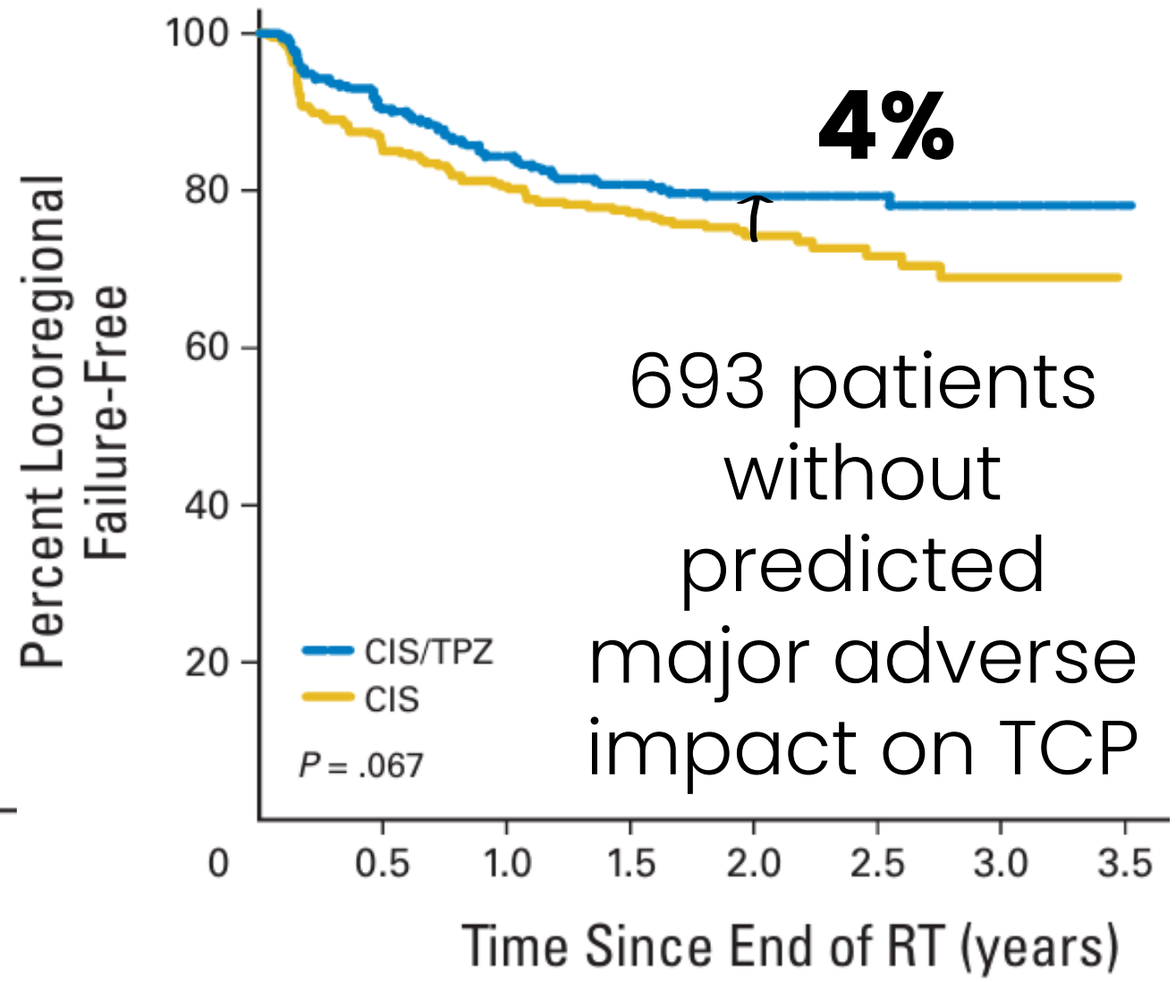


Is Plan Quality Crucial?

- Power to detect **10% improvement** in 2-year Overall Survival (OS) attributable to Tirapazamine (TPZ)





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Is Plan Quality Crucial?

- Poor RT can **outweigh benefits** of concurrent chemotherapy
- Comparisons of combined modalities may be **compromised** by poor RT
- **Quality varies** across countries <u>but the mor imortant</u>
- Correlates with **center size**:
  - 5.4% poor RT plans → ≥20 patients/center
  - 29.8% poor RT plans → <5 patients/center
- Trial participation should be **limited to high-volume sites**

Quality Assurance in Trials

- **Test the center**, not just individual RT plans
- Ensures consistent **standards and reliability** across sites

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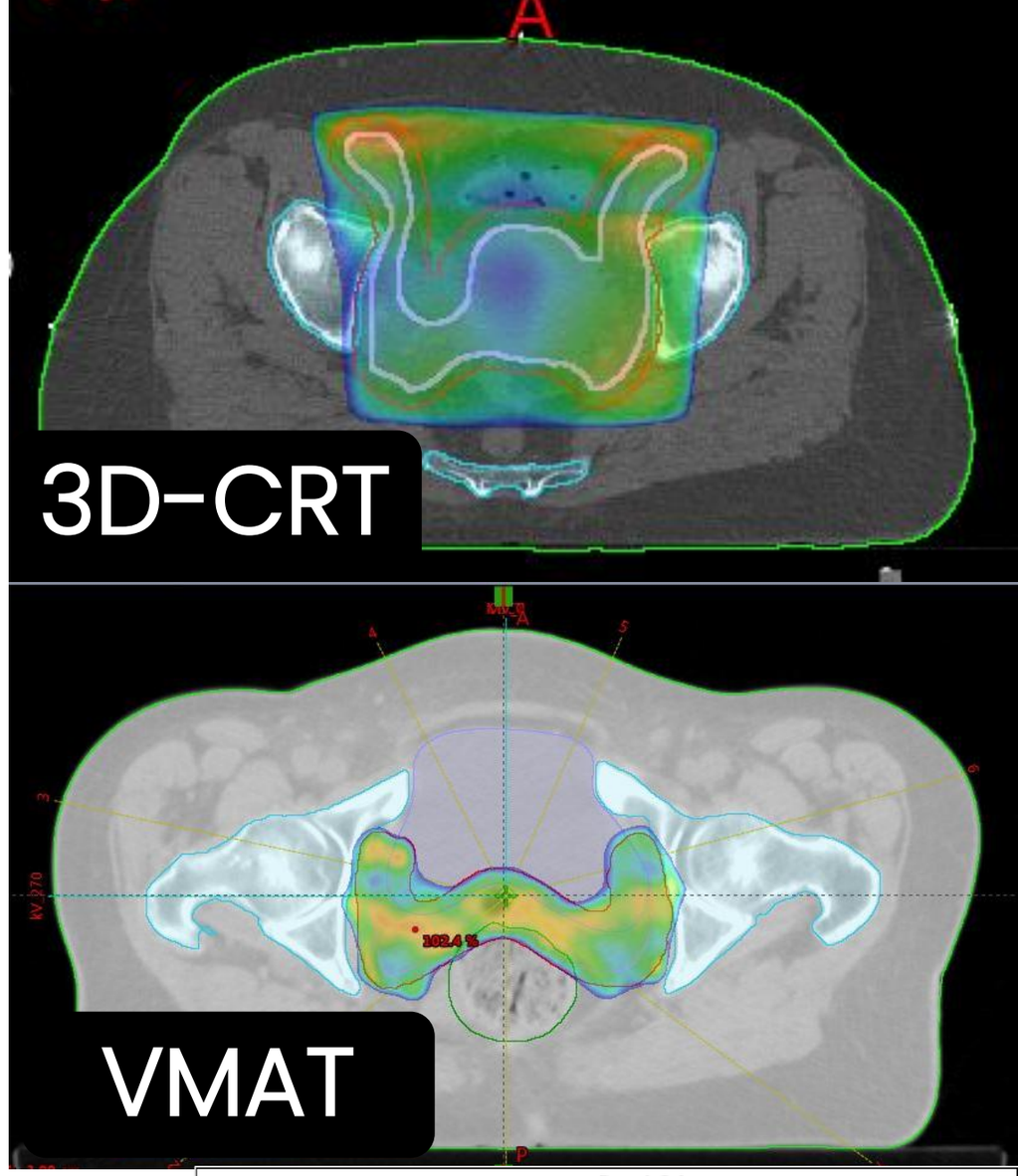
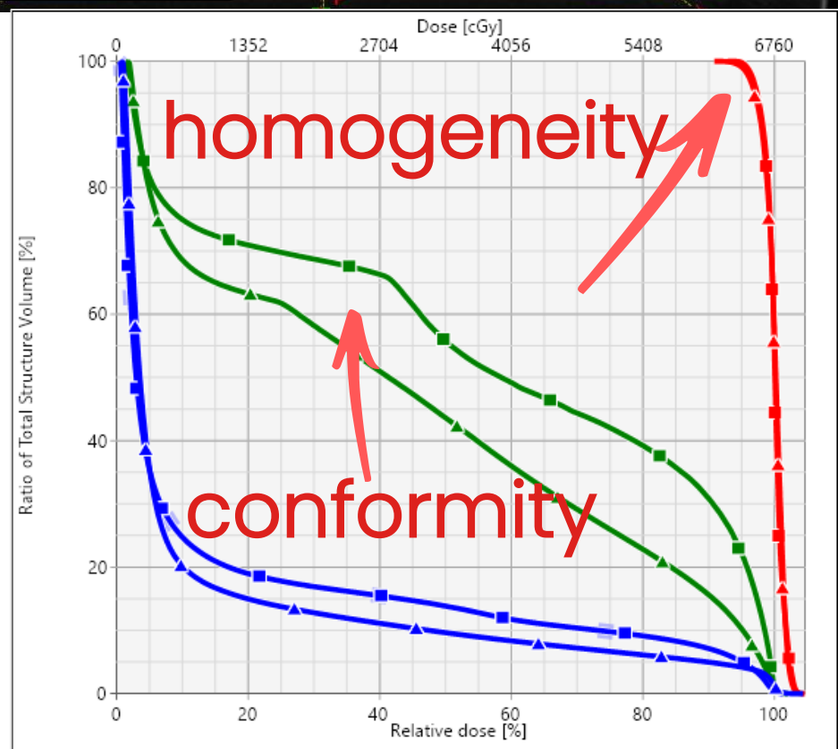
Have Dynamic Techniques Accelerated Planning?

- Inverse planning: complex *balance → tumor coverage vs. OAR sparing*
- Highly computerized, but still **resource-intensive** *manual, labor-intensive, planner-dependent*
- Requires **expertise & experience** for high-quality plans





3D-CRT
VMAT

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Why automation?

Advantages of automation

- Increased **efficiency & consistency**
- Reduced **inter-planner variability**
- Fewer **errors**
- Supports **Adaptive Radiotherapy (ART)**

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Why automation?

Potential Risks of automation

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Main automation approaches (Treatment Planning Focus)

- Knowledge-Based Planning (KBP)
- Protocol-Based Automatic Iterative Optimization (PB-AIO)
- Multicriteria Optimization (MCO)
- Fully Automated Planning
- Adaptive Radiotherapy (ART & oART)

KNOWLEDGE-BASED PLANNING (KBP)

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Knowledge-Based Planning (KBP)

- **prior knowledge -** use knowledge from prior cases to predict the outcome of a new case

- learn the **relationships between anatomical structures and dose** distributions

  ➔ provides **one or more dose metrics** as a starting points for plan optimization
  ➔ **predict DVHs** as a starting point for plan optimization
  ➔ **predicts achievable dose** for new patients with similar anatomy

- improve the **speed, efficiency and reduce** variability in treatment planning

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Knowledge-Based Planning (KBP) - Methods

- **atlas-based** approach
  - selects the closest matching patient(s)
  - better starting point

- **model-based** approach - DVH-guidance
  statistical or ML trained on a database of prior high-quality plans

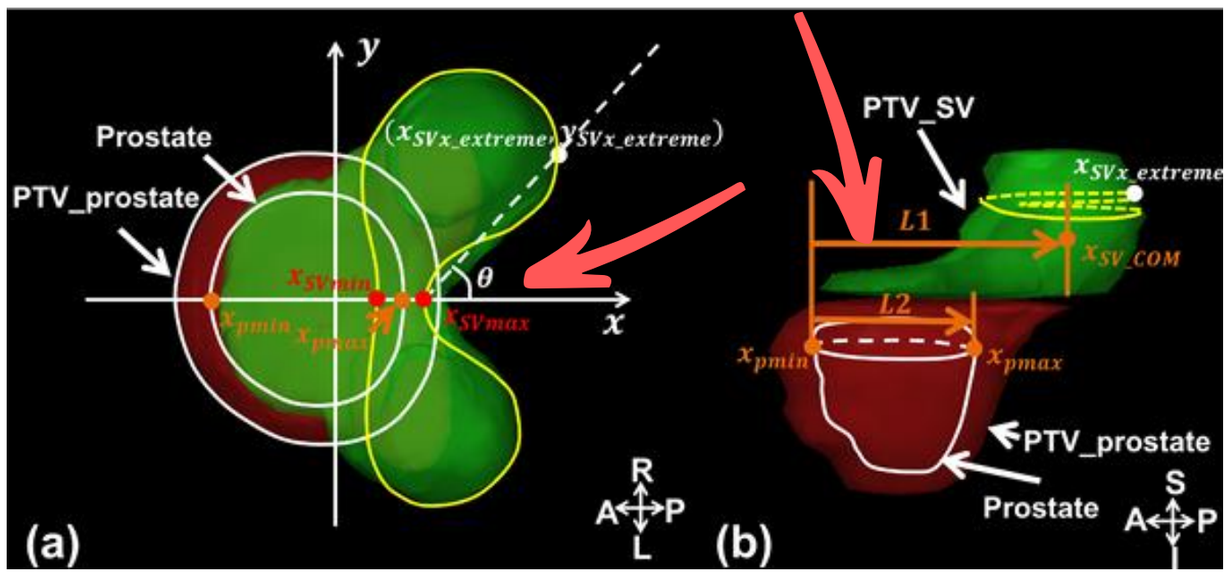
➔ statistical methods
Support vector regression, multivariate linear regression, Logistic Regression etc.

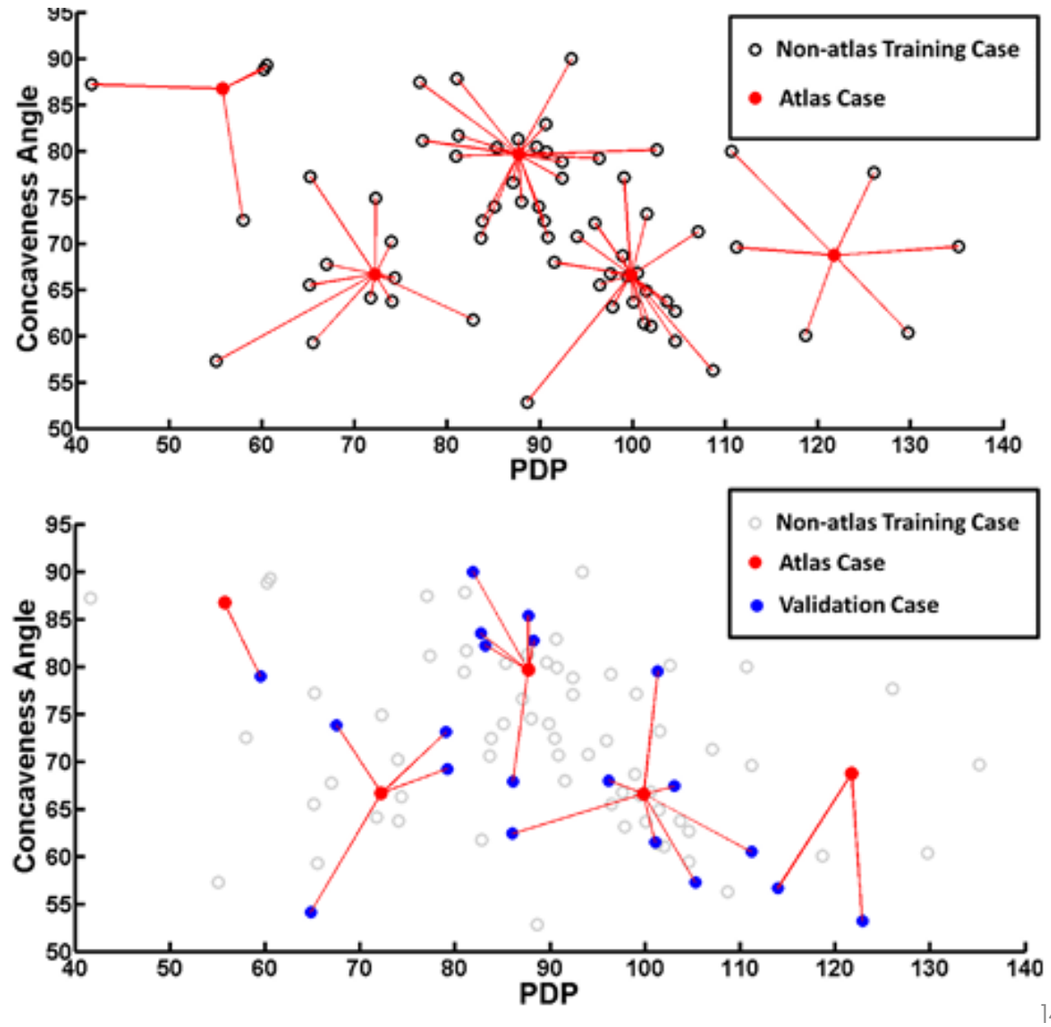
➔ machine learning (ML) method
random forests, support vector machines (SVMs), neural networks

KBP atlas-based approach

- Adaptive Radiotherapy (ART) - inter-fractional variation for a single patient -> refines adaptive plans using a reference (single atlas) plan
- Inter-patient variation - reference case from a library

Example

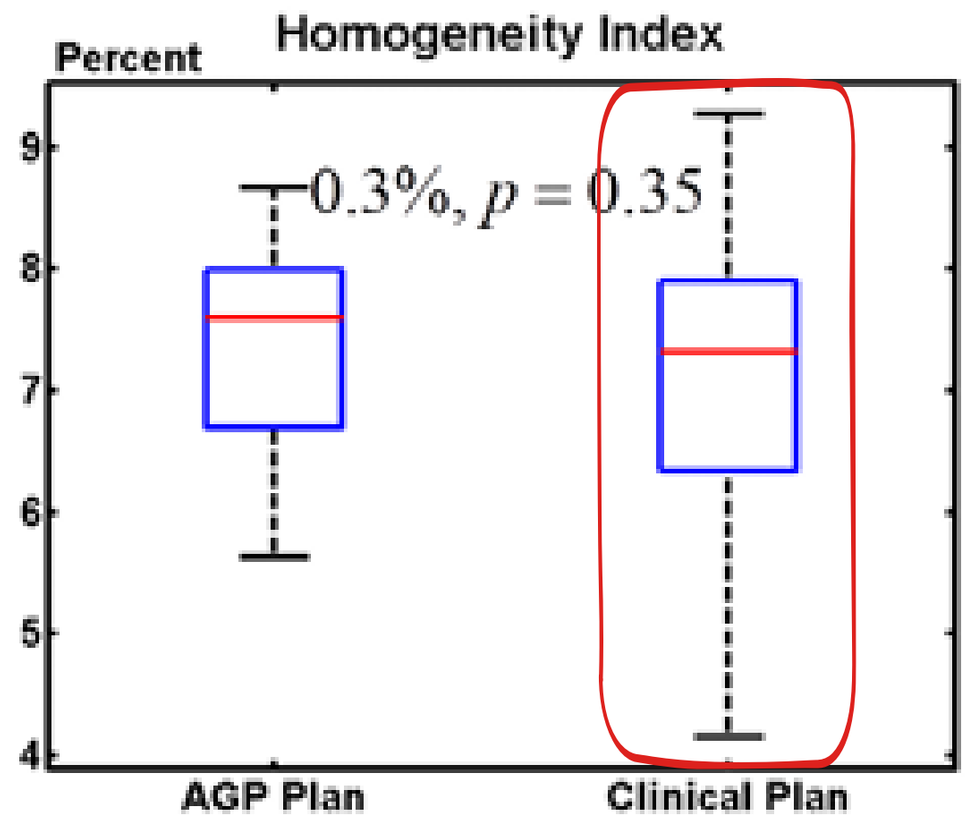


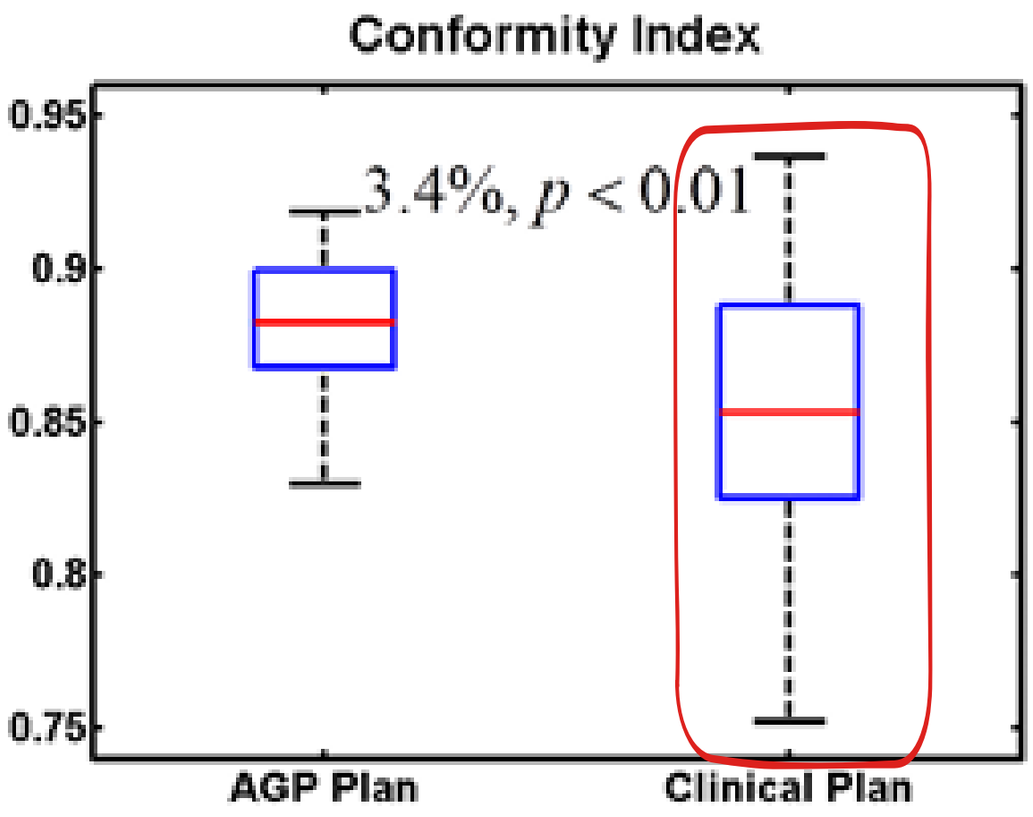


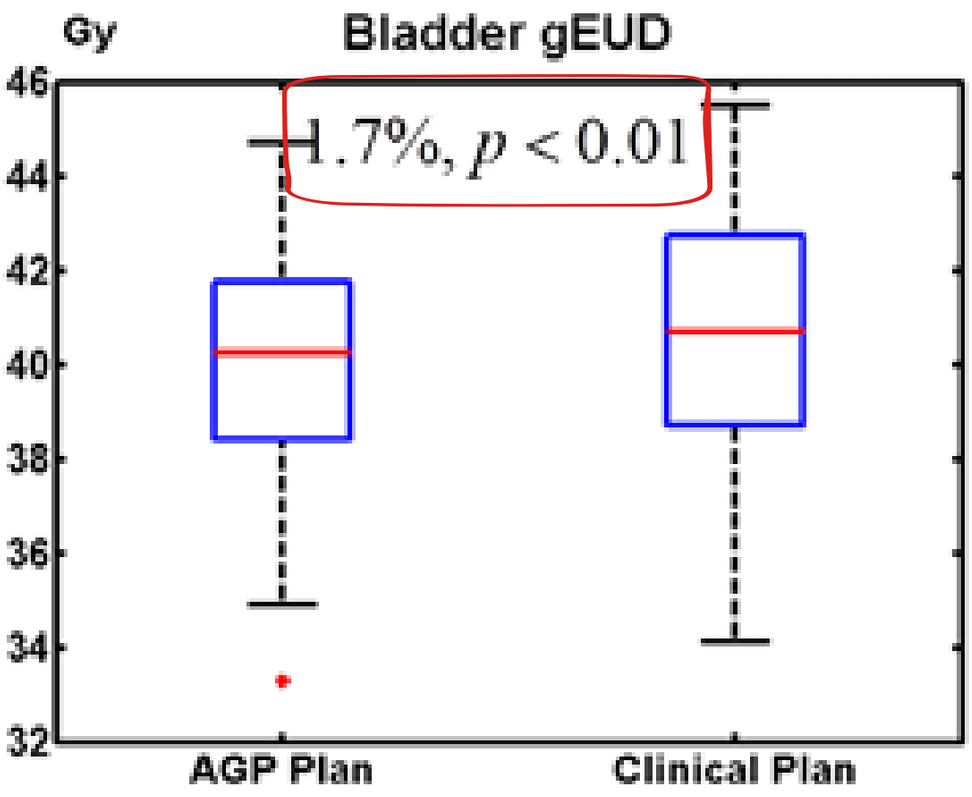
goals imported into Eclipse TPS

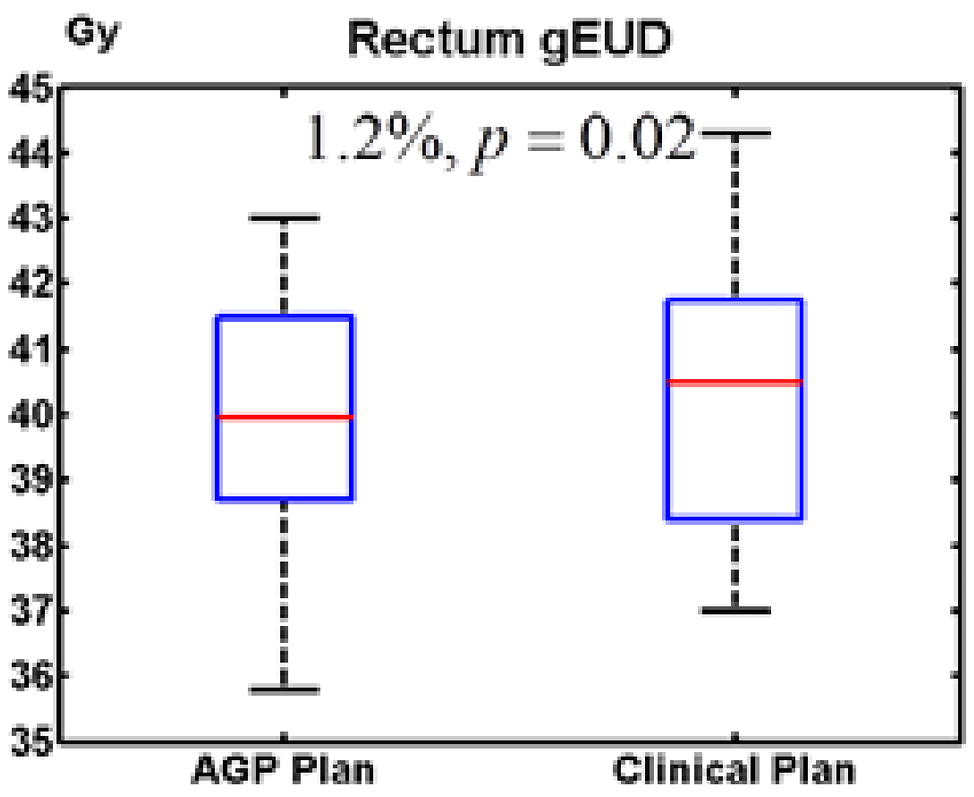
Sheng et al. Phys. Med. Biol. 60 (2015) 7277–7291
doi:10.1088/0031-9155/60/18/7277

KBT atlas-based approach









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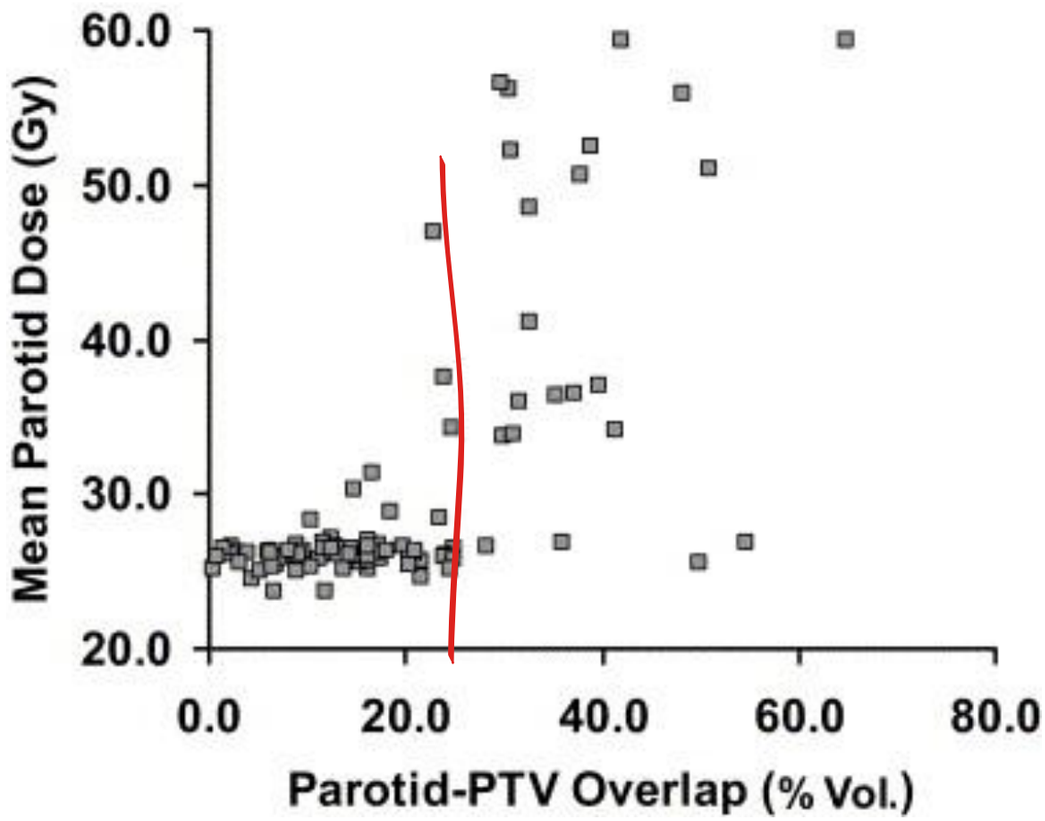
Knowledge-Based Planning (KBP)

Traditional KBP methods

1. anatomical and geometrical features
   distance to target structures, volumes of target and OAR, BEV, overlap PTV-OAR, ML-based approach, shape analysis etc.)

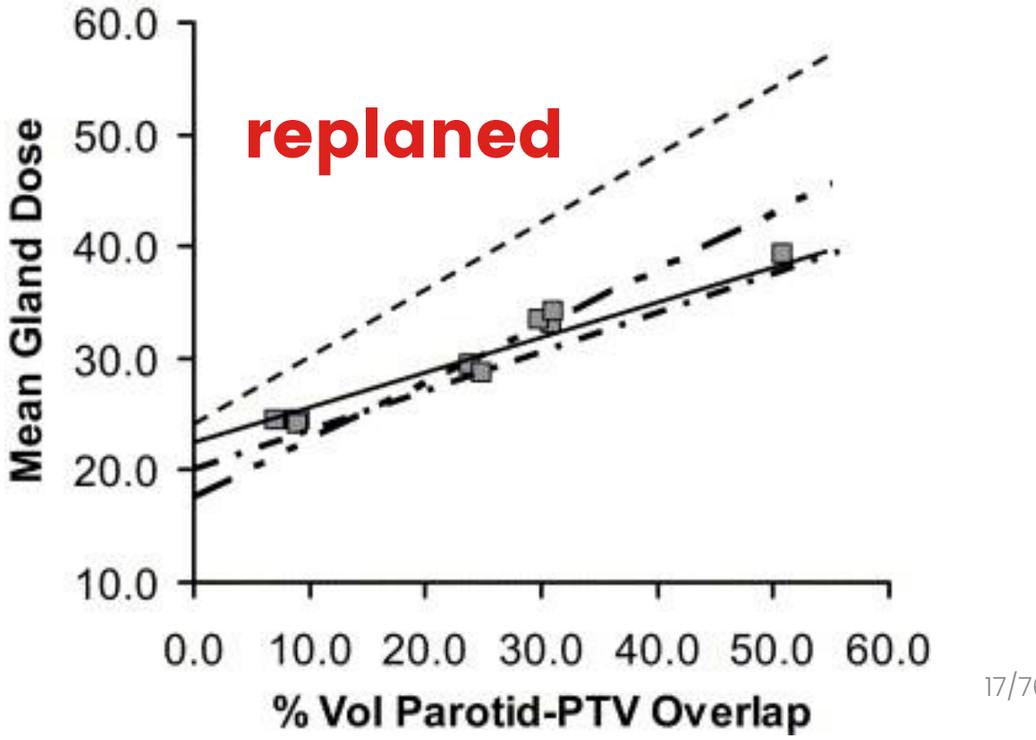
Commonly reported geometric and plan features

- OAR, PTV - volume, shape
- OAR distance to PTV
- Target, OARs - overlap volumes
- Volume of OAR out-of-field
- OVH - overlap volume histogram
- DTH - OAR distance to PTV histograms
- BEV (Projection-based method)



Example

- Prediction of the achievable parotid sparing
  -> parotid size and proximity to the PTV (Hunt, 2006)
- $MPD[Gy] = \frac{\%V_{IN} \cdot D_{IN}}{100} + \frac{\%V_{OUT} \cdot D_{OUT}}{100}$



https://doi.org/10.1016/j.ijrobp.2006.05.028

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Dimensionality Reduction in KBP

- Use **most discriminative features**, not all variables
- **Feature extraction & selection** streamline prediction models
- PCA (Principal Component Analysis):
  - ➔ Reduces correlated dataset → fewer uncorrelated variables, reduces dimensionality
  - ➔ Keeps most informative variables
- Commonly applied in **KBP dose prediction studies**

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2. build a mathematical or statistical model to predict dosimetry features to new case

I) prediction of one or more DVH metrics
II) prediction of the entire DVH (*RapidPlan, Varian, Eclipse, 2014*)
III) voxel-based dose prediction

Outliers and Database Size

- Outliers can compromise model performance
- **Geometric outliers** – prostate vs prostate with nodes
- **Dosimetric outliers** – possible reduction OAR dose without PTV compromising - <u>re-planning needed</u>

- Clinic **without standardized contouring** and planning techniques may have **many dosimetric outliers**

Knowledge-based plan	Oral Cavity (Gy)	C. Parotid (Gy)	I. Parotid (Gy)
$Model_{UC}$	20.5±8.4	16.8±5.2	19.9±6.5
$Model_{C}$	20.6±9.0	16.7±5.2	19.9±6.5
$Model_{5}$	20.3±8.5	16.3±5.6	19.2±6.3*
$Model_{10}$	21.1±9.7	16.2±5.5	19.0±6.4
$Model_{15}$	20.1±8.5	18.0±7.2	20.2±7.4
$Model_{20}$	20.0±8.5	18.1±7.3	20.4±7.9
$Model_{25}$	20.0±8.5	18.6±7.6	21.0±7.8
$Model_{30}$	19.6±8.4	20.2±7.7*	21.1±7.6
$Model_{35}$	19.6±8.2	18.4±6.5	23.0±7.7*
$Model_{40}$	19.6±8.2	21.1±8.9*	23.8±8.8*

UC – uncleaned, C – cleaned, 5-40 outliers

Delaney *Int J Radiat Oncol Biol Phys*. 2016;94:469-477. https://doi.org/10.1016/j.ijrobp.2015.11.011

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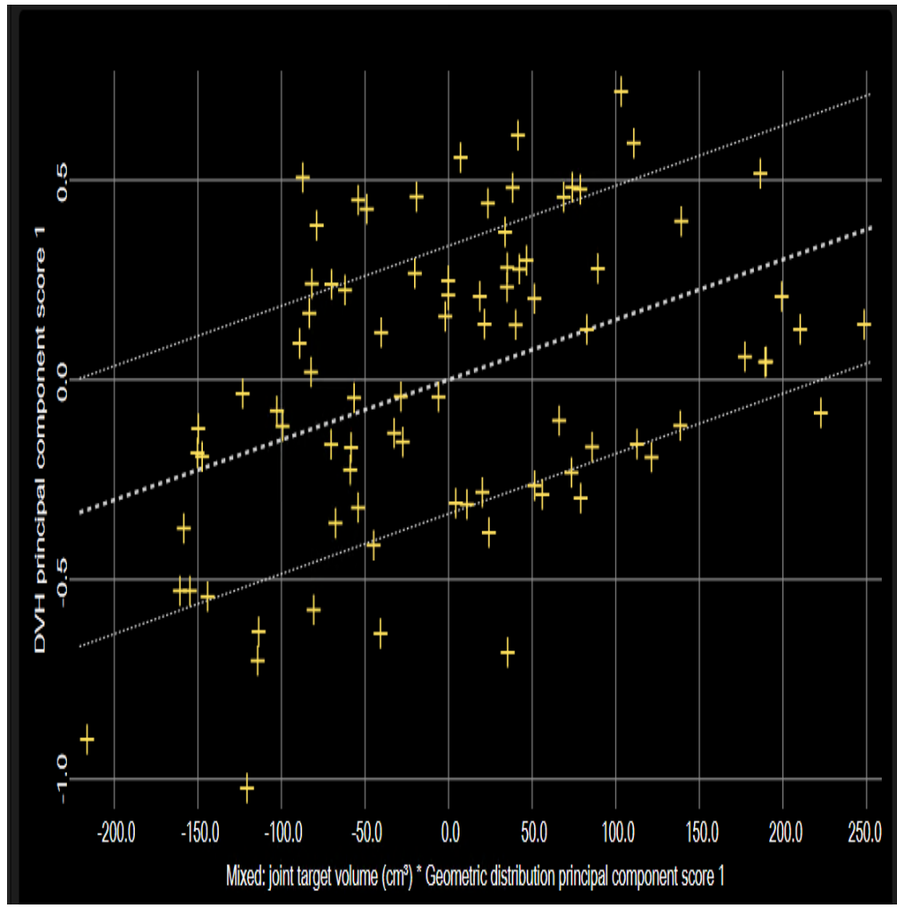
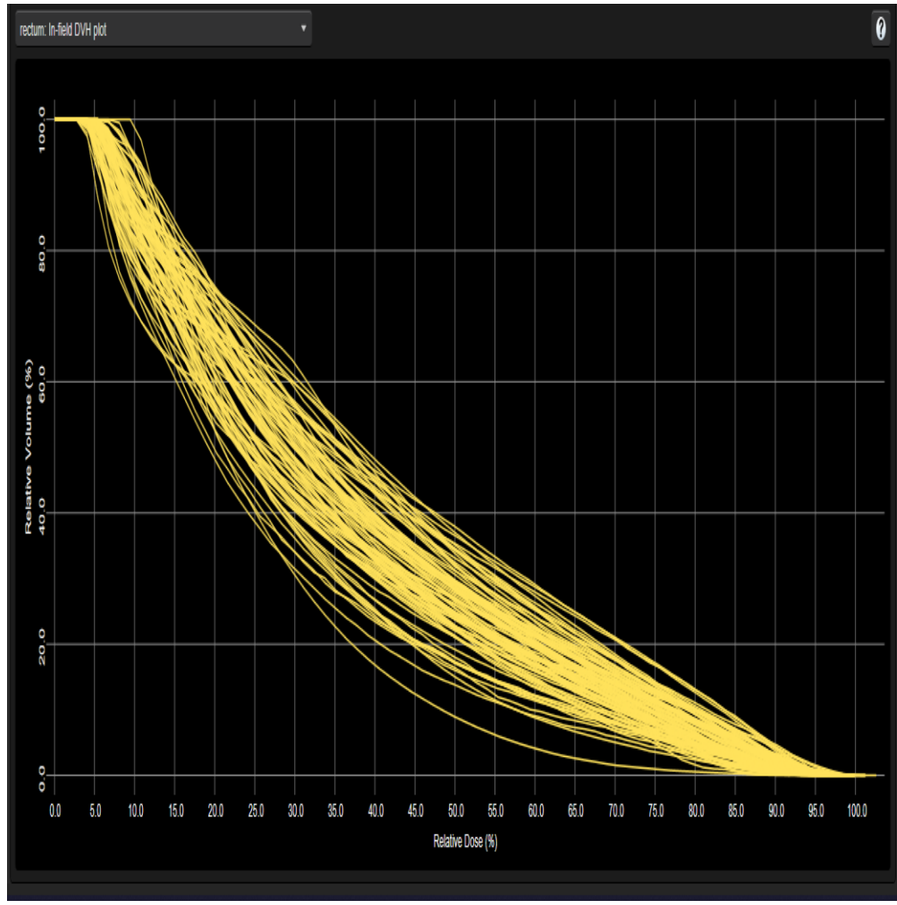
Diversities of application

- **Fully automate** Rapid Plan **treatment planning** of 10 different cancer sites (Chung et al., 2025)
- **Photon → Proton**: DVH prediction as **patient selection tool** (Delaney et al. 2017)
- **Cooperative models:** Sharing between institutes in prostate cancer (Schubert et al., 2017)
- **Knowledge transfer:** Prostate model from experienced → less experienced centers to **homogenize plan quality** (Good et al., 2013)
- **Clinical trials:** NRG-HN001 Rapid Plan model used for **QA,** improving OAR sparing in re-optimized trial plans (Giaddui et al., 2020)

RapidPlan Model Creation

1. Data Collection *(manual)*
   - User selects and imports high-quality treatment plans
2. Feature Extraction *(automatic)*
   - System extracts geometric & dosimetric features from dataset.
   - Performs **dimensionality reduction (PCA)** automatically.
3. Model Training *(automatic)*
   - Regression/statistical learning links features with DVHs.
   - System generates **dose–volume predictions** + optimization objectives.
4. Validation *(manual + automatic)*
   - User selects independent cases.
   - System runs predictions → user verifies accuracy.





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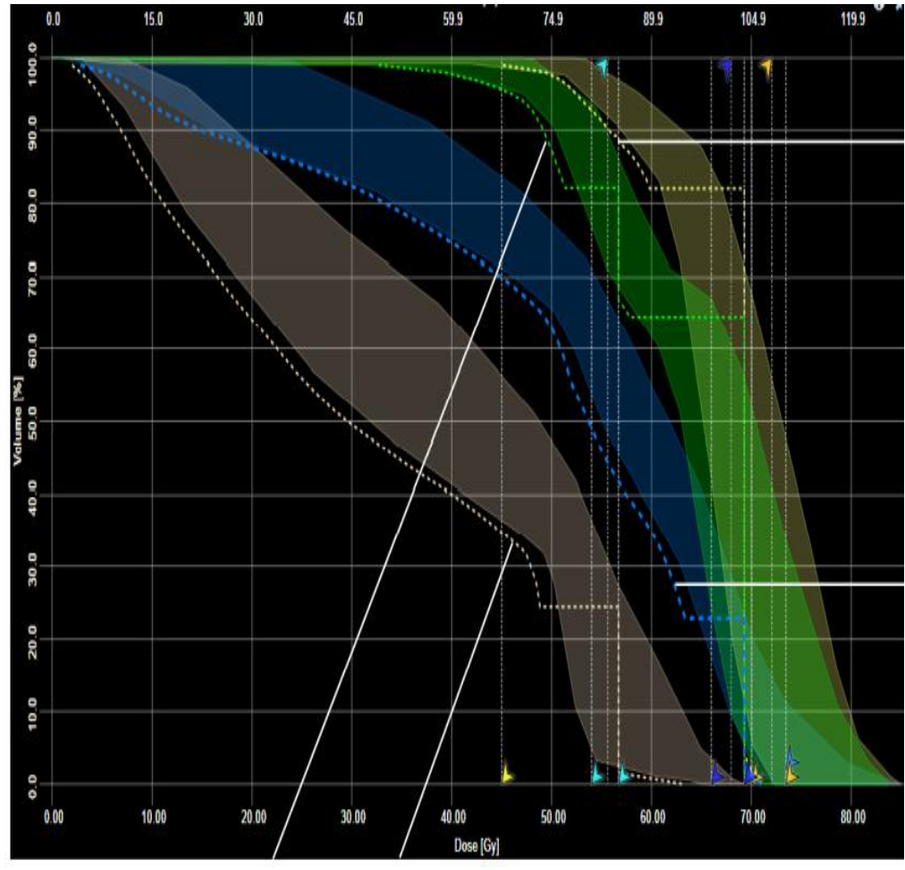
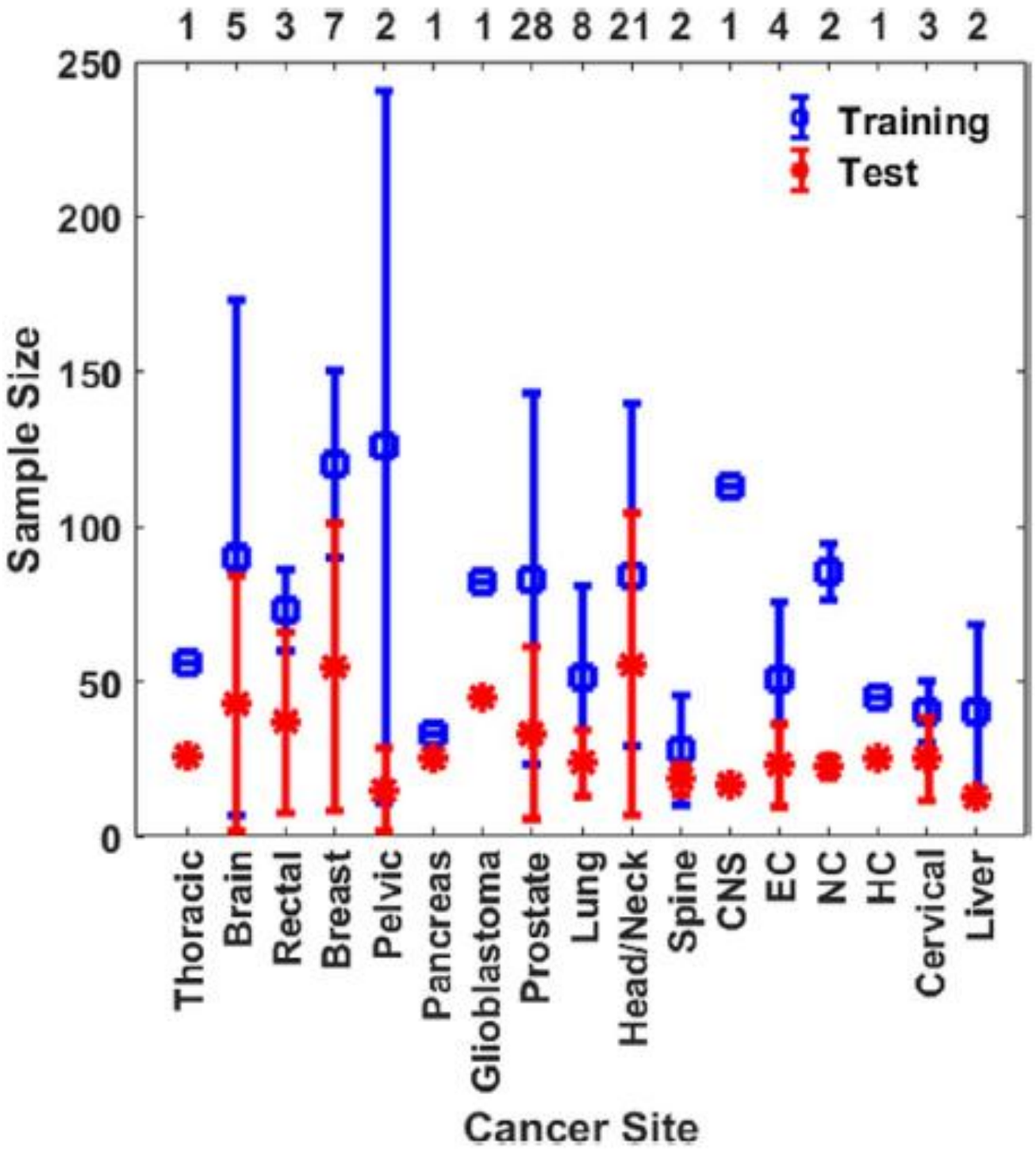


Sample size



- **minimum number** of plans required for model creation - **20**
- with high-quality plans in training 25–30 plans prostate (Fogliat, 2014) and HN (Tol, 2015) may produce a clinically acceptable plan
- Depends on expected robustness

Momin, *J Appl Clin Med Phys*, 2021. https://doi.org/10.1002/acm2.13337

Efficiency

- nasopharyngeal cancer: **64 minutes vs. 295 minutes** (Change)
- malignant pleural mesothelioma **20 min. vs. 4 hours** (Dumane, 2021)

Table 1. Average times for manual and automated planning for each anatomical site.

Model name	Average time manual planning (min)	Average time RapidPlan planning (min)	Percentage decrease in planning time
CNS	178	38	78.7%
LungSBRT	185.3	38.3	79.3%
Oesophagus	100	40	60.0%
LiverSBRT	622	28.75	95.4%
Rectum	1137.5	53.89	95.3%
Anus	720	40	94.4%
Gynae	805	50	93.8%
Bladder	300	42.5	85.8%
Prostate	390.7	44	88.7%
Prostate + LN	456.7	91	80.1%
Average	489.5	46.6	90.5%

Junior et al., 2022, **https://doi.org/10.23925/1984-4840.2022v24i1/4a7**

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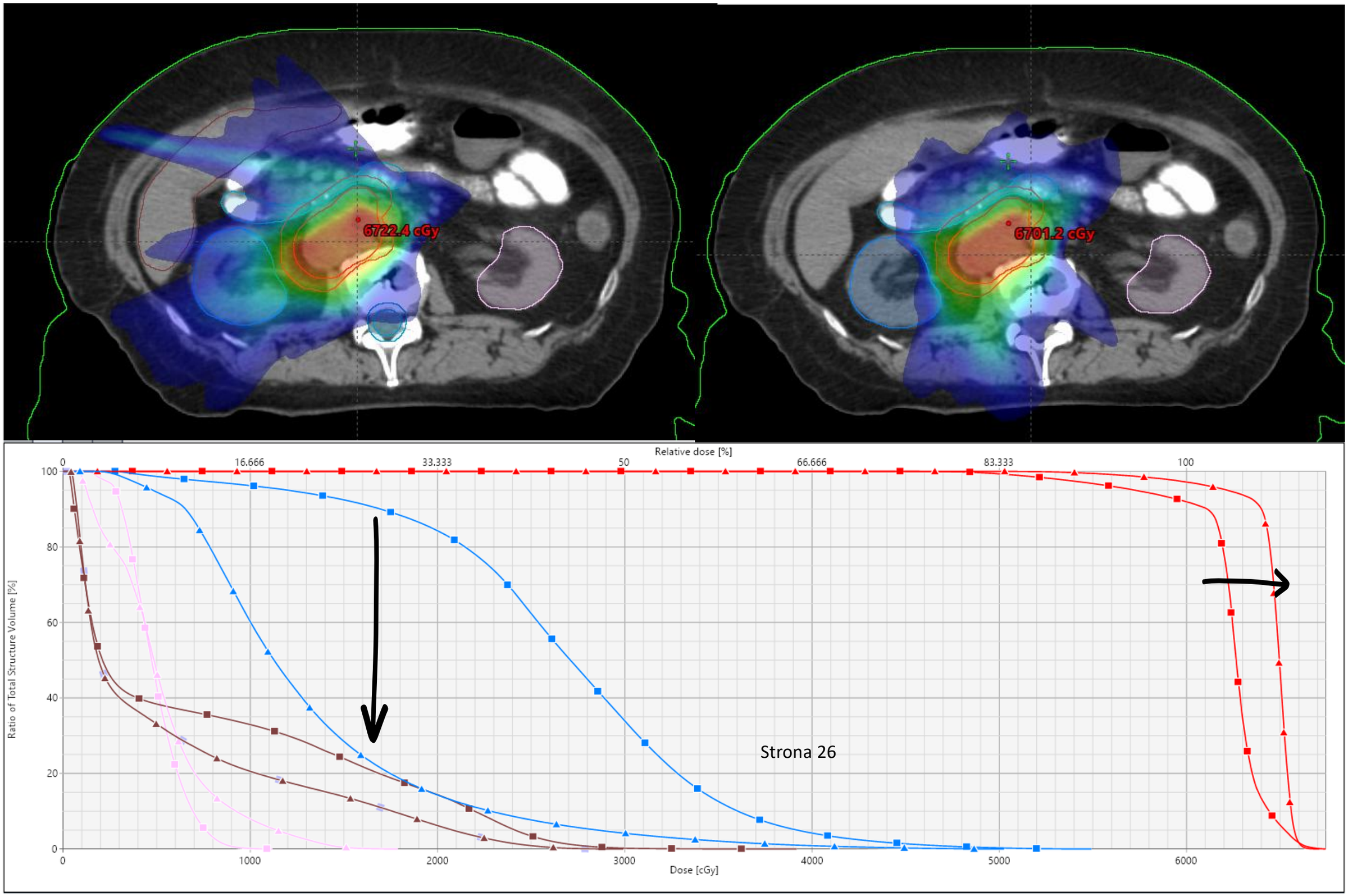
Rapid Plan – Model



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Deep learning (DL)-based KBP methods

Key difference: traditional vs. DL

- traditional -> uses handcrafted prior knowledge
- DL -> learns patterns directly from raw data

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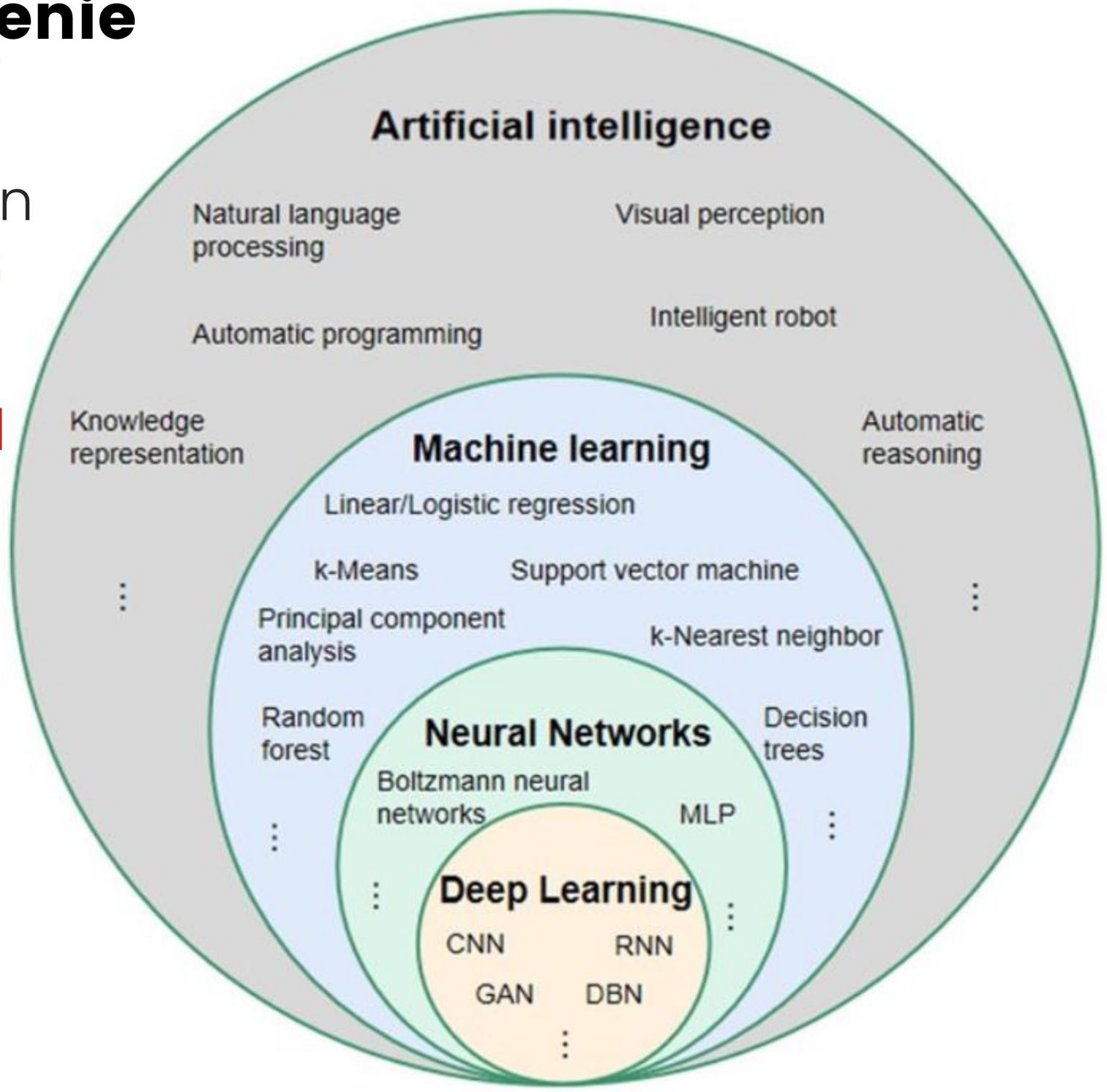
Szybkie wprowadzenie

- MLP
  multilayer perception
- **CNN**
  convolutional neural network (U-Net, ResNet-50)
- DBN
  deep belief network
- GAN
  generative adversative network
- RNN
  recurrent neural network



Machine learning (ML)
Deep learning (DL)

Diagnostics 2021, 11, 1523. doi.org/10.3390/diagnostics11091523

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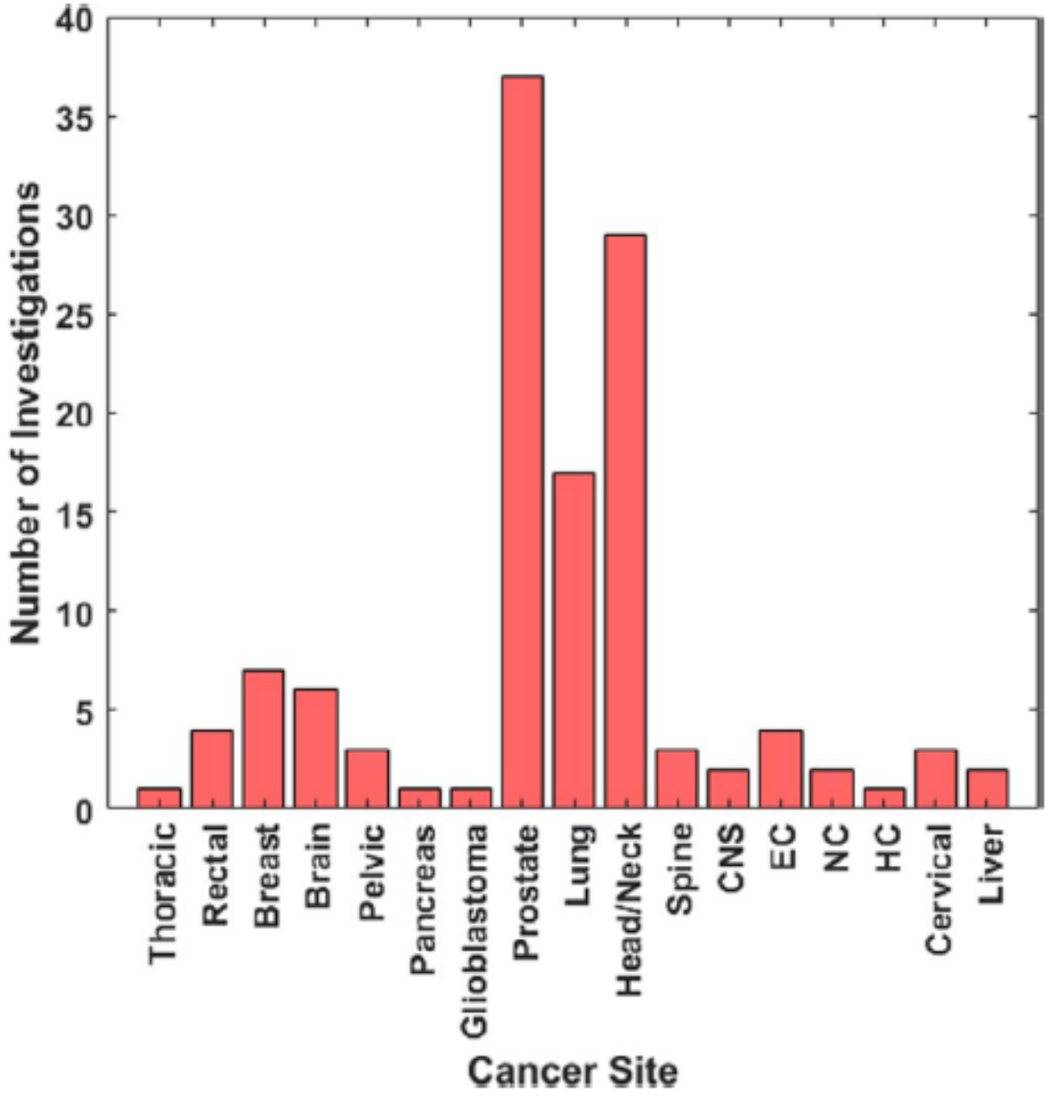
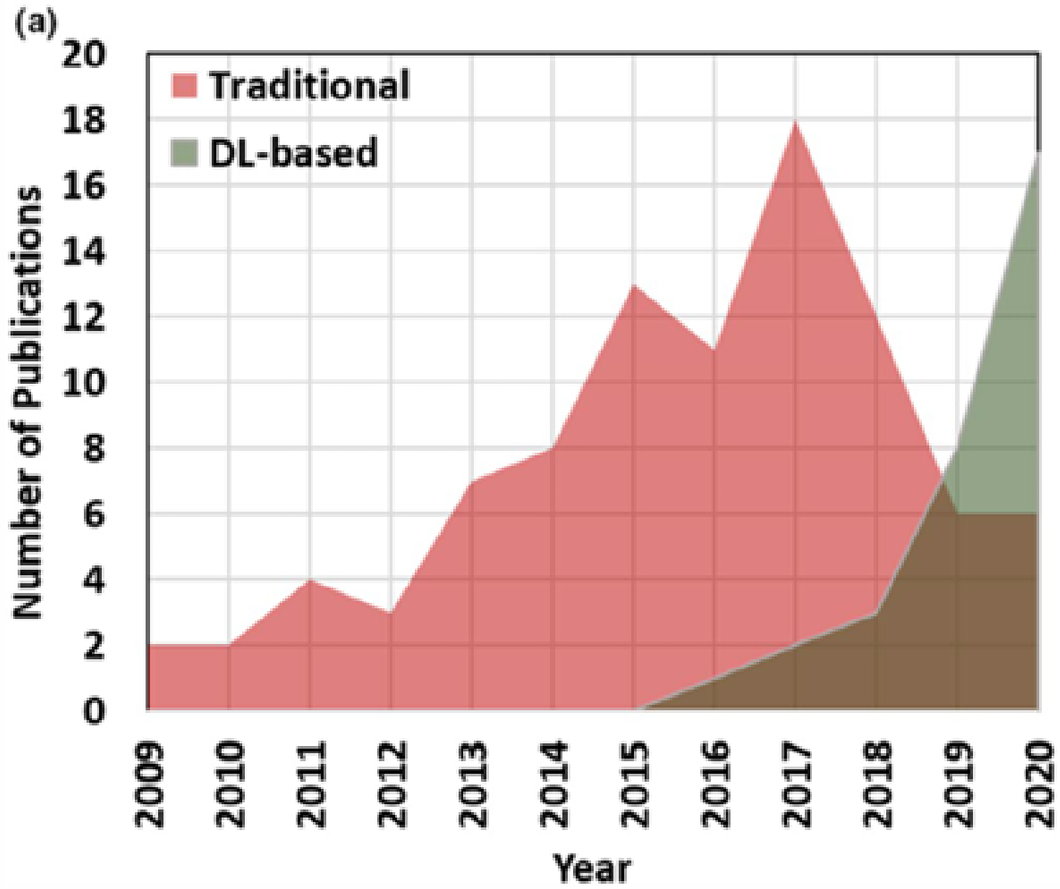
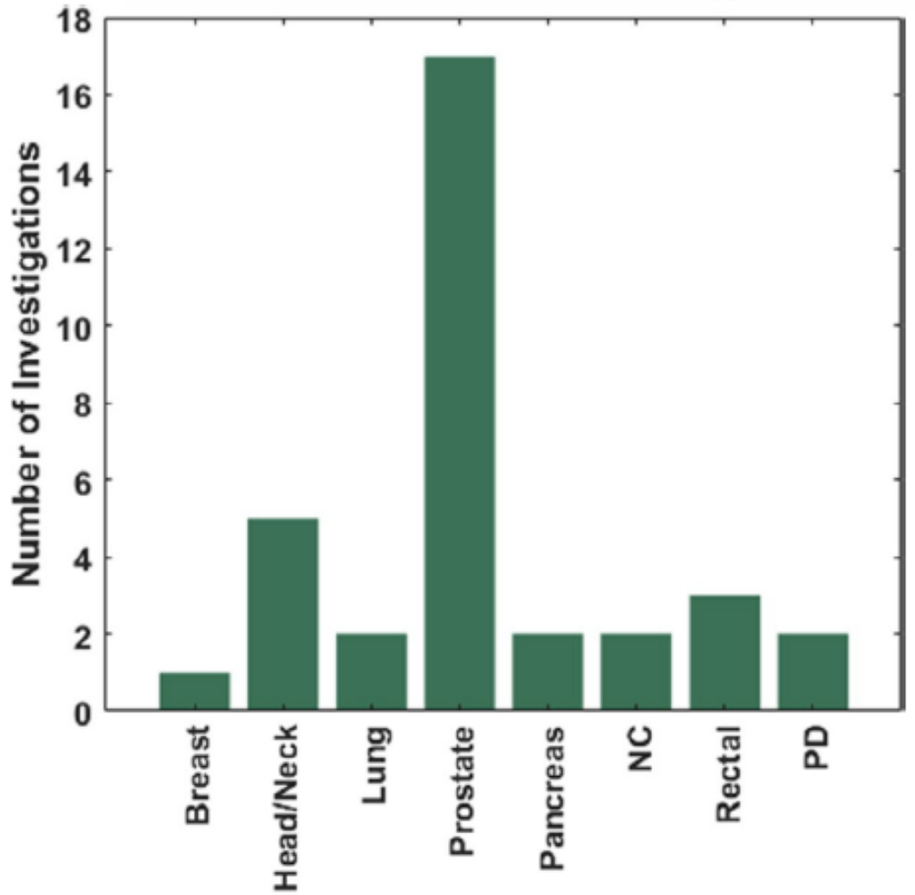
Knowledge-Based Planning (KBP)

August 2020







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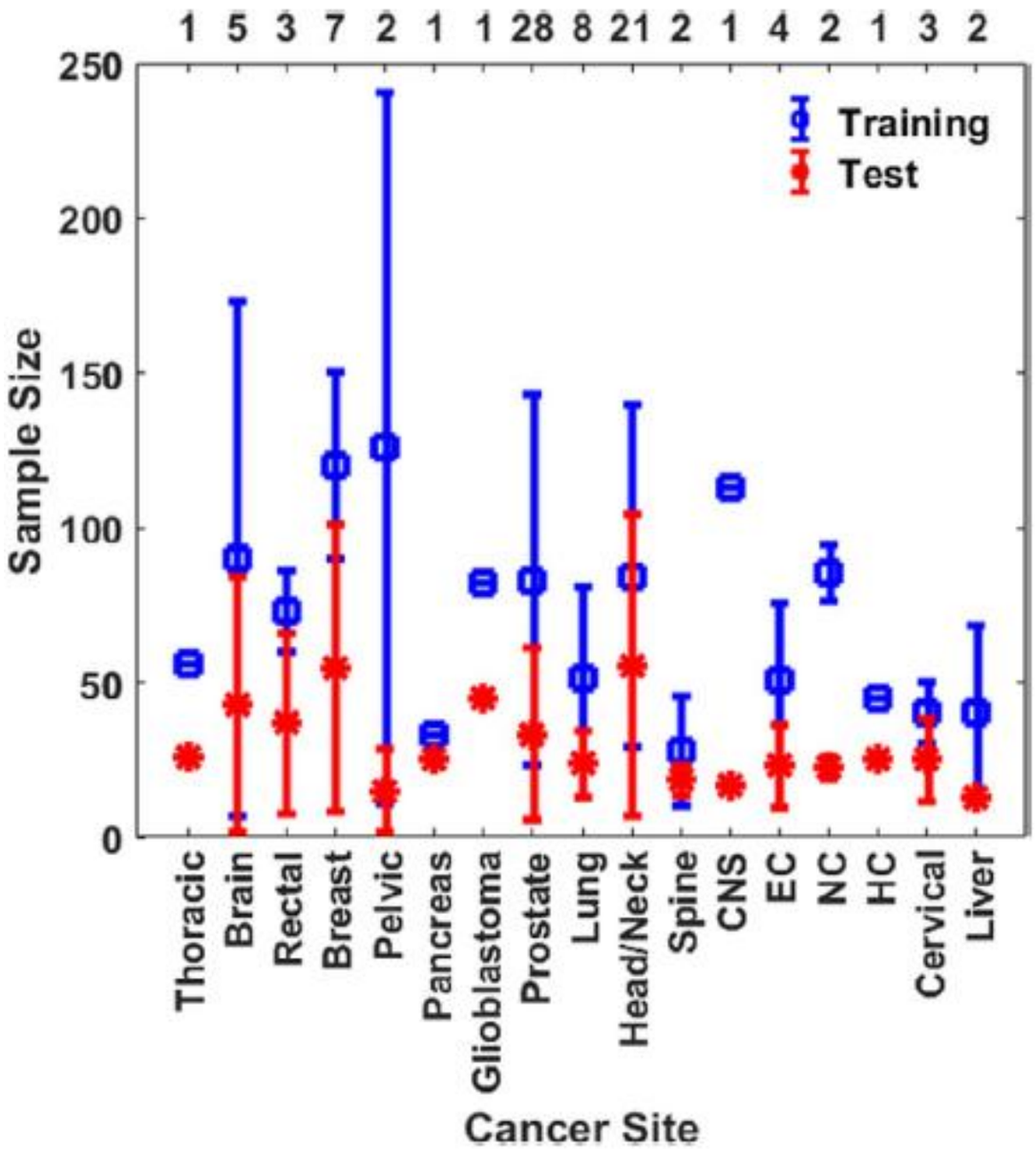
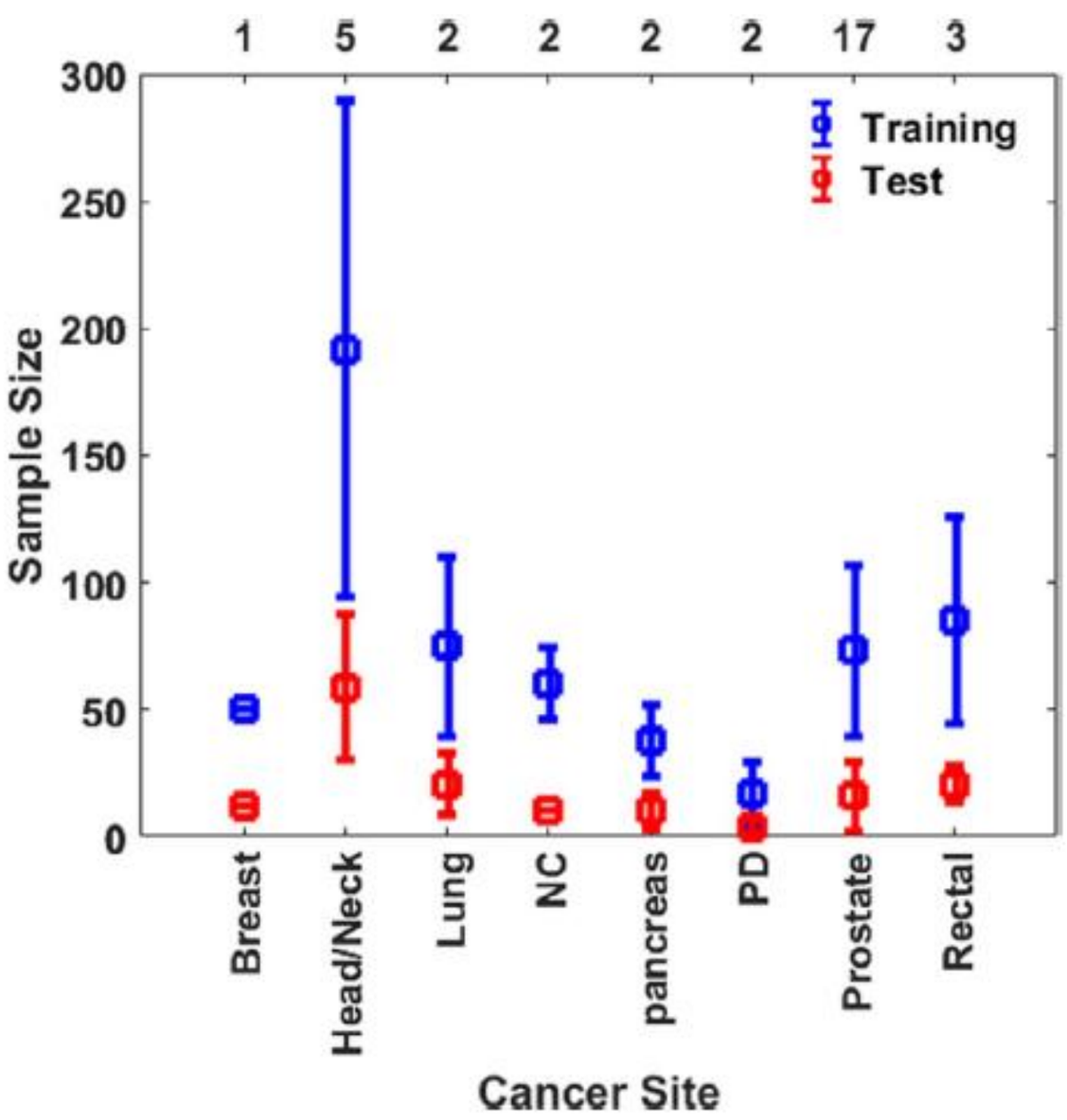
Sample size





- Small datasets in DL can be challenging as it may result in overfitting.
- Data Augmentation, dropout layer, estimation based on the training and the validation curves etc.

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Advantages

- Improve **consistency & efficiency**
- Reduce **inter-planner variability**
- Facilitates **standardization** across centers

Limitation

- Predictions only for **implemented ROIs**
- **DVHs lack spatial information** → voxel-based methods
- Plan quality strongly depends on **quality of past plans**

Challenges

- **Outliers** in training data
- Database **size & quality**
- Generalization to **unusual anatomies**
- Validation & **QA** of models
- **Interpretability** of predictions

PROTOCOL-BASED AUTOMATIC ITERATIVE OPTIMIZATION

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Protocol-Based Auto-Planning

Idea

- Uses clinical rules/protocols coded as algorithm (Example: IMRT/VMAT plans per QUANTEC, RTOG guidelines)
- Does not require prior plans

Advantages

- Transparent – rules are explicit
- Easy to adapt to local standards

Limitations

- Less flexible in complex cases
- Struggles with unusual clinical scenarios

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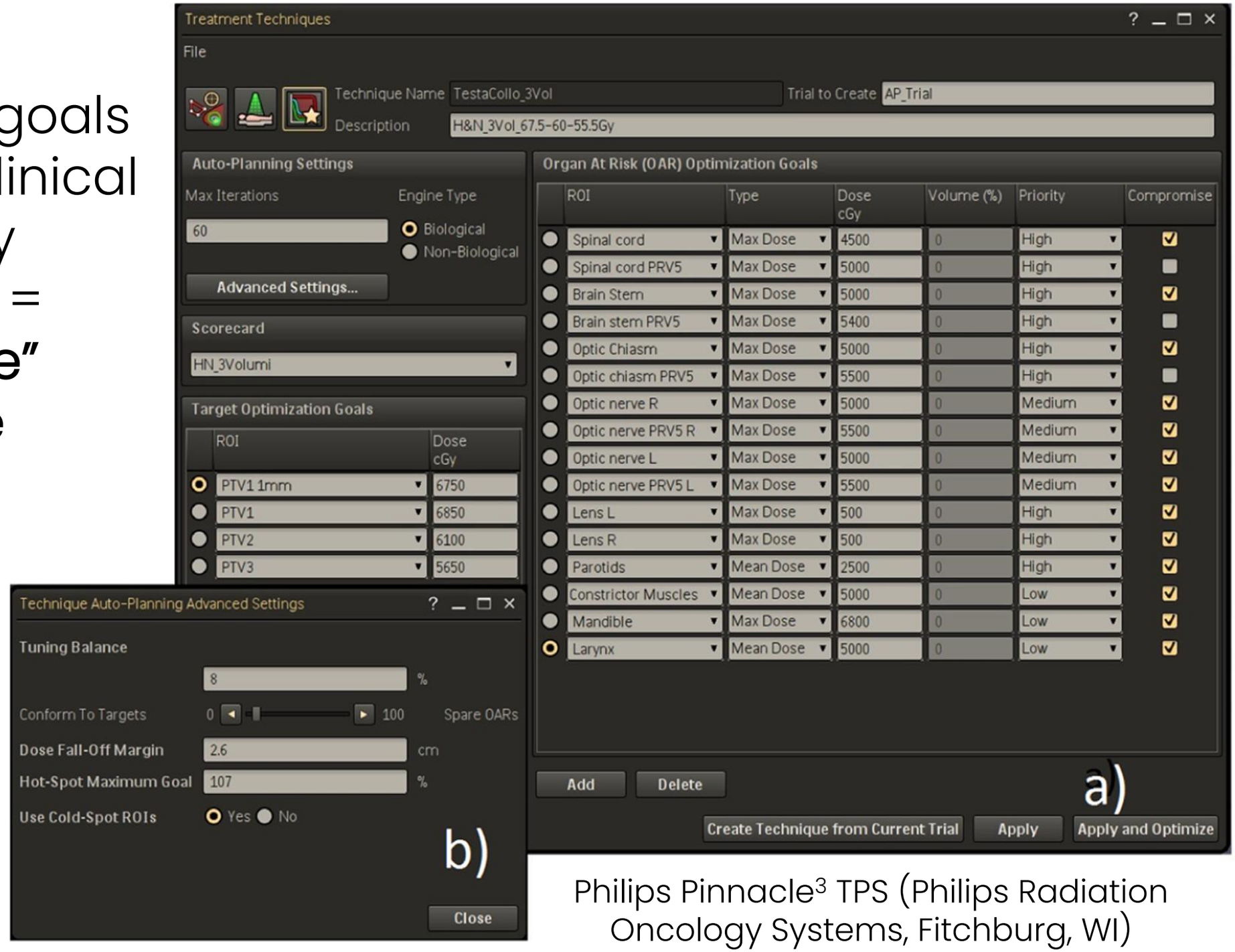
Pinnacle³ Auto-planning

User-defined goals aligned with clinical dosimetry standards = **“Technique”** template



Philips Pinnacle³ TPS (Philips Radiation Oncology Systems, Fitchburg, WI)

Cilla, Scientific Reports 2020, https://doi.org/10.1038/s41598-019-56966-y
Gintz, J of Applied Clinical Medical Physics 2016, https://doi.org/10.1120/jacmp.v17i3.6167

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Pinnacle³ Auto-planning

The user

- **Template** with target prescriptions and OAR goals (clinical protocol)
- **OAR priorities** weighted by clinical importance

The software

- Creates **helper structures** (rings, overlaps) to guide optimization
- Controls **dose fall-off, homogeneity, hot/cold spots**
- Provides **initial optimization criteria**
- Runs **iterative optimization cycles** to meet protocol goals

- a global Plan Quality Index (PQI)

What makes it “Auto-Planning” is the **automation of goal generation, structure creation, and iterative refinement**, not a new optimizer per se.

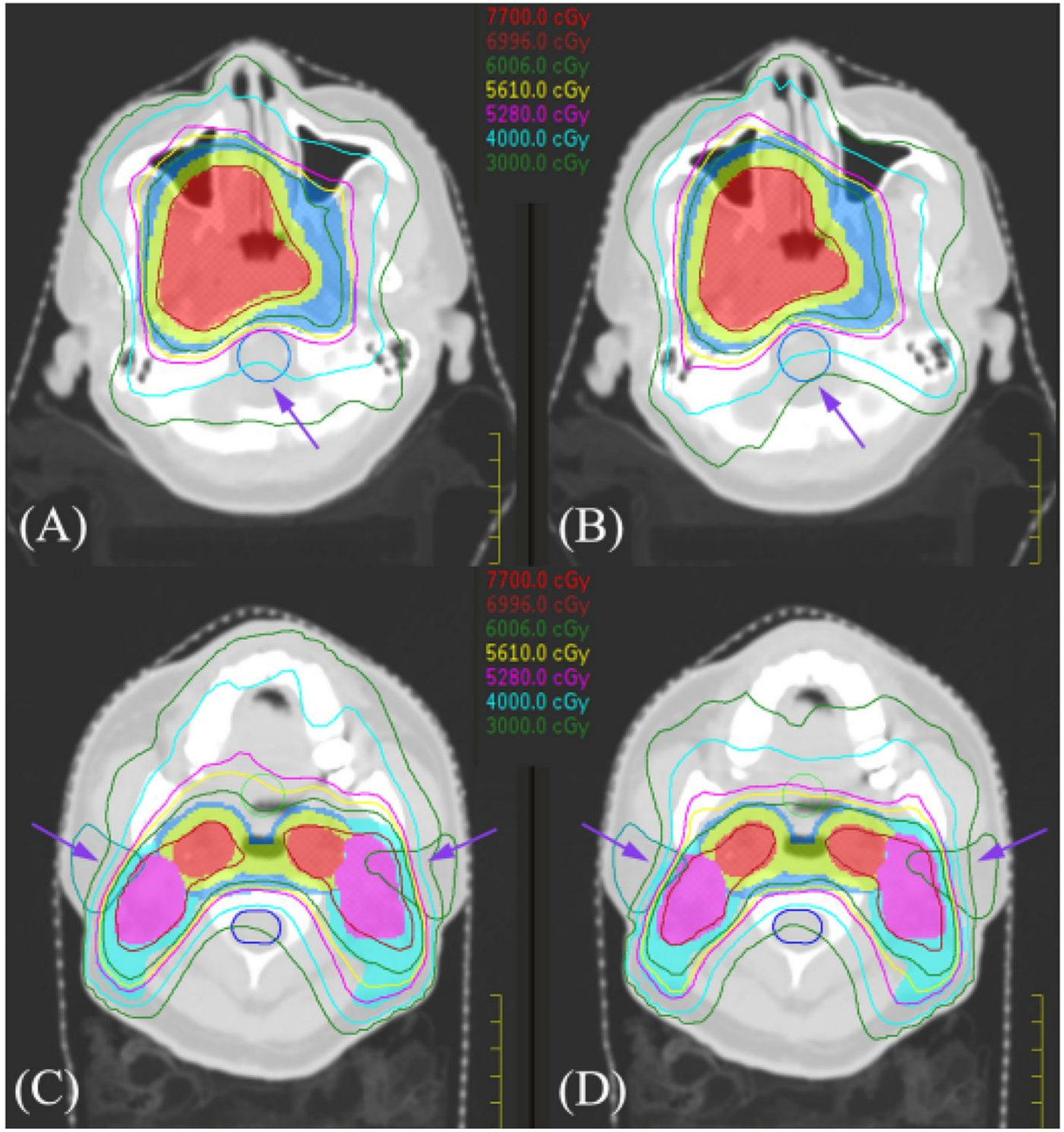
Pinnacle³ Auto-planning

TABLE 1. The starting technique (AP 1).

ROI	*Goal Type*	*D (Gy)*	*V (%)*	*Priority*	*Compromise*
PTV_70	Target Dose	70		-	-
PTV_70+1 mm	Target Dose	70		-	-
PTV_56	Target Dose	57		-	-
Parotid (L and R)	Mean Dose	23		High	Yes
Parotid (L and R)	Max DVH	10	50	Medium	Yes
Cord	Max Dose	40		High	No
Cord + 5 mm	Max Dose	50		High	No
Brainstem	Max Dose	48		Medium	No
Brainstem + 3 mm	Max Dose	50		Medium	No
Oral cavity	Max Dose	28		High	Yes
Mandible	Max Dose	71		High	Yes
Inferior Pharyngeal Constrictor	Mean Dose	39		Medium	Yes
Superior/Middle Pharyngeal Constrictor	Mean Dose	51		Medium	Yes
Glottic and Supraglottic Larynx	Mean Dose	48		Low	Yes
Submandibular glands	Mean Dose	39		Low	Yes
Cerebellum	Max DVH	50	1	Low	Yes
Ring tuning structure around PTVs	Max Dose	71		Medium	Yes
Ring tuning structure around PTVs	Max DVH	56	25	Medium	Yes

Gintz, J of Applied Clinical Medical Physics 2016, https://doi.org/10.1120/jacmp.v17i3.6167

Pinnacle³ Auto-planning



For locally advanced NPC, **Auto-Planning** could generate VMAT **plans with similar or superior plan quality** compared to manual VMAT plans for most patients

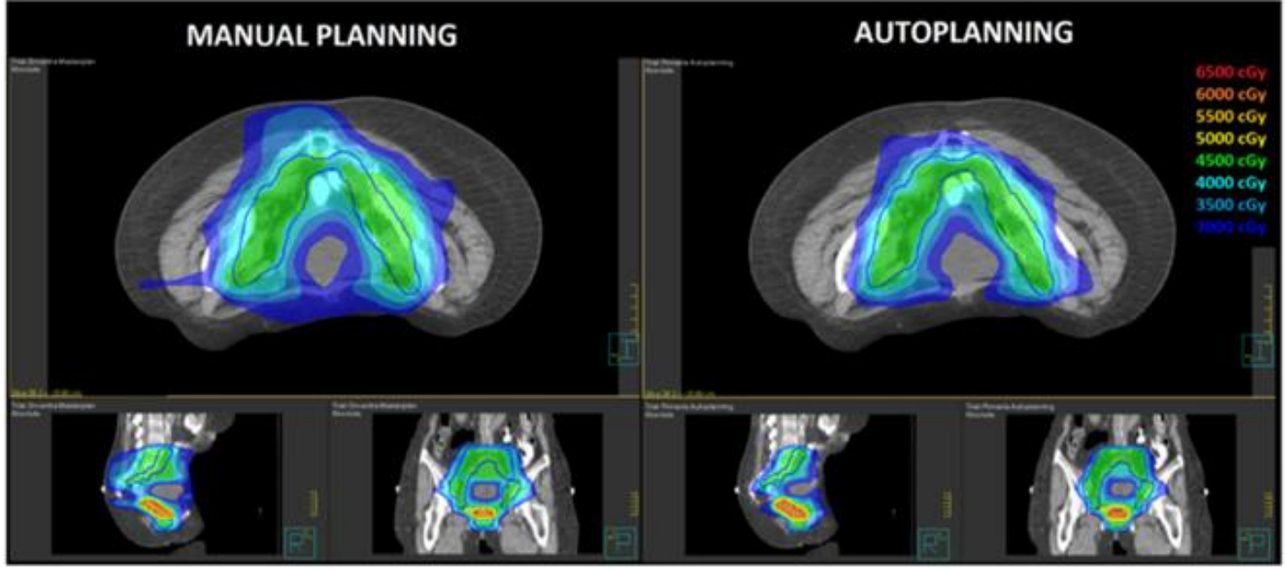
manual approach could be preferred in **stage IV** patients, due to a better control of the balance between the OARs and targets by **an experienced physicist**

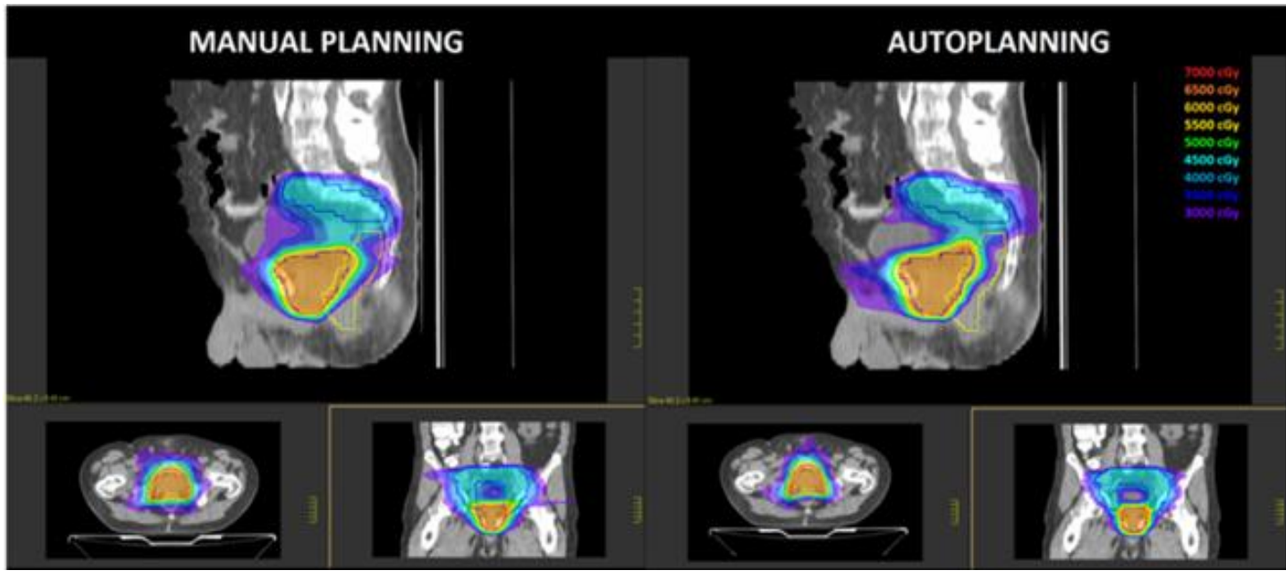
Chen Jihong, Sci Rep 2022, **https://doi.org/10.1038/s41598-022-07519-3**

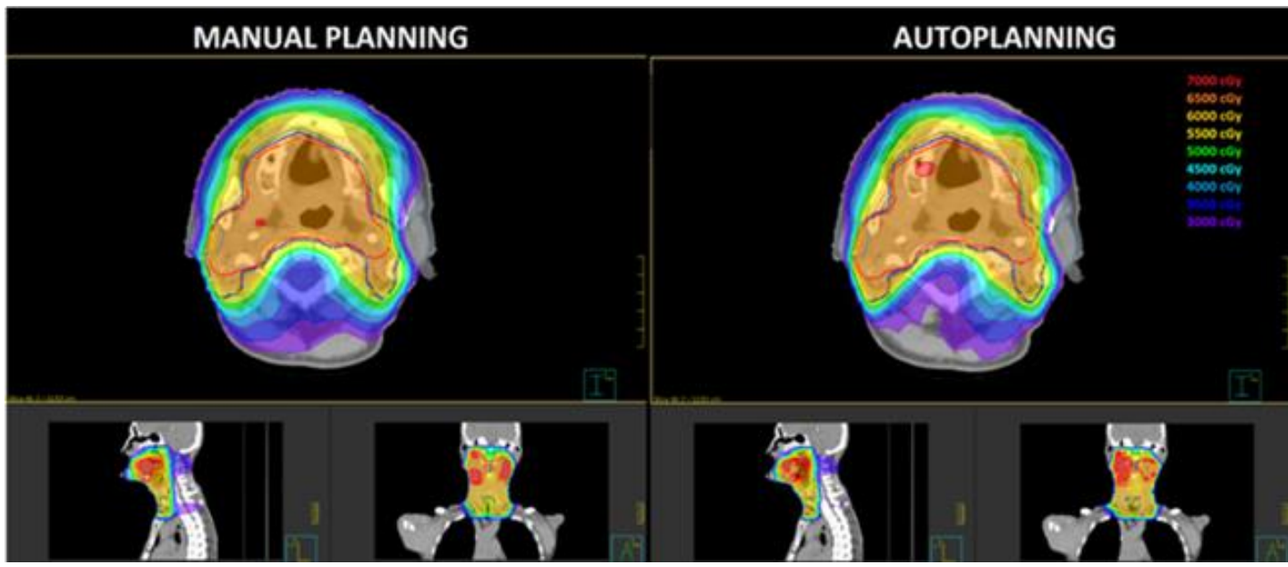
Narodowy Instytut Onkologii

Pinnacle³ Auto-planning

- Produces high-quality, clinically acceptable plans
- Improves overall treatment quality
- ↑ Dose conformity
- ↓ Integral dose (6–10%)
- Maintains target coverage
- Cuts planning time to 60–80 min (~⅓)
- 94% of plans scored equal or better in clinical review



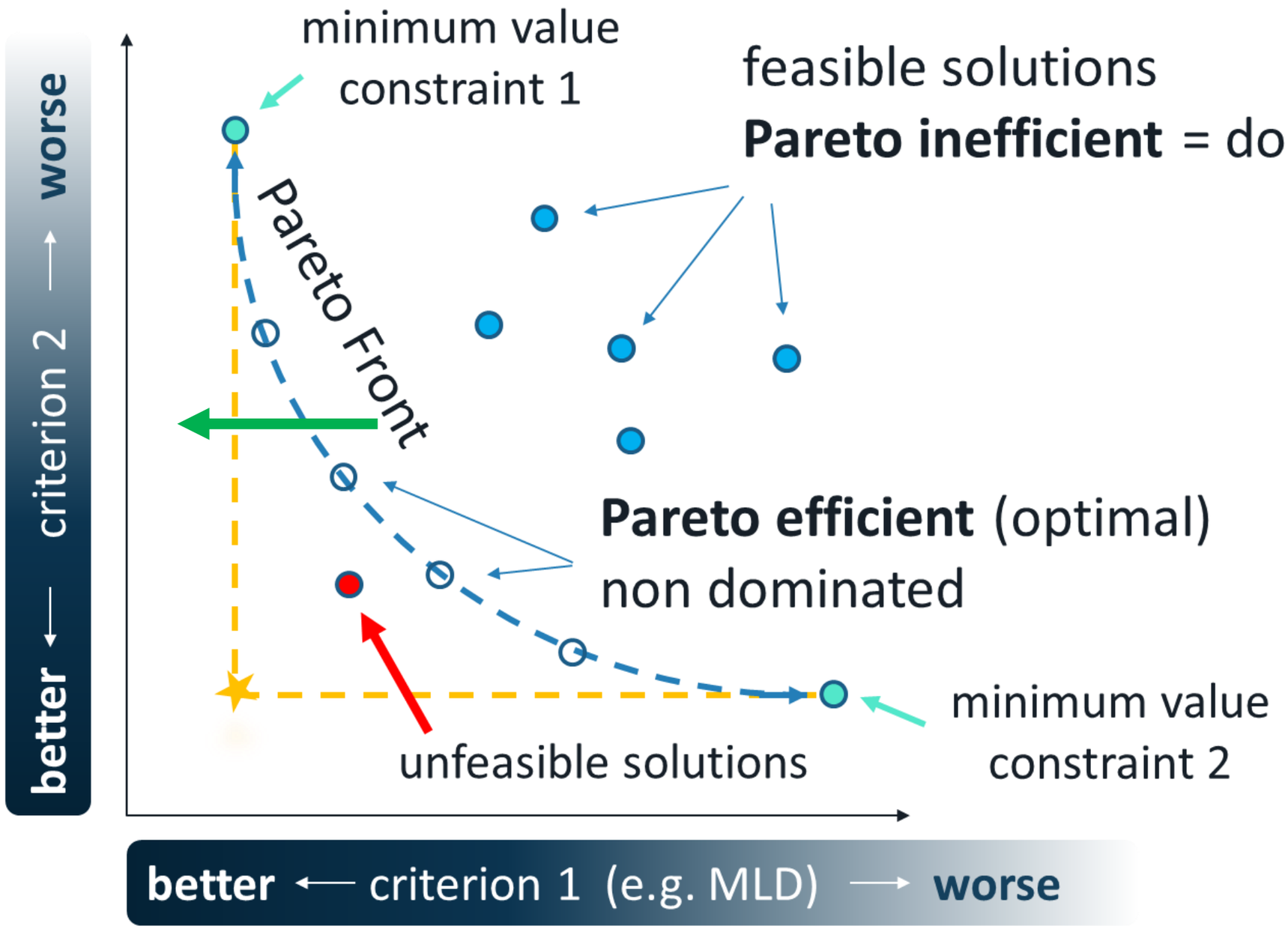




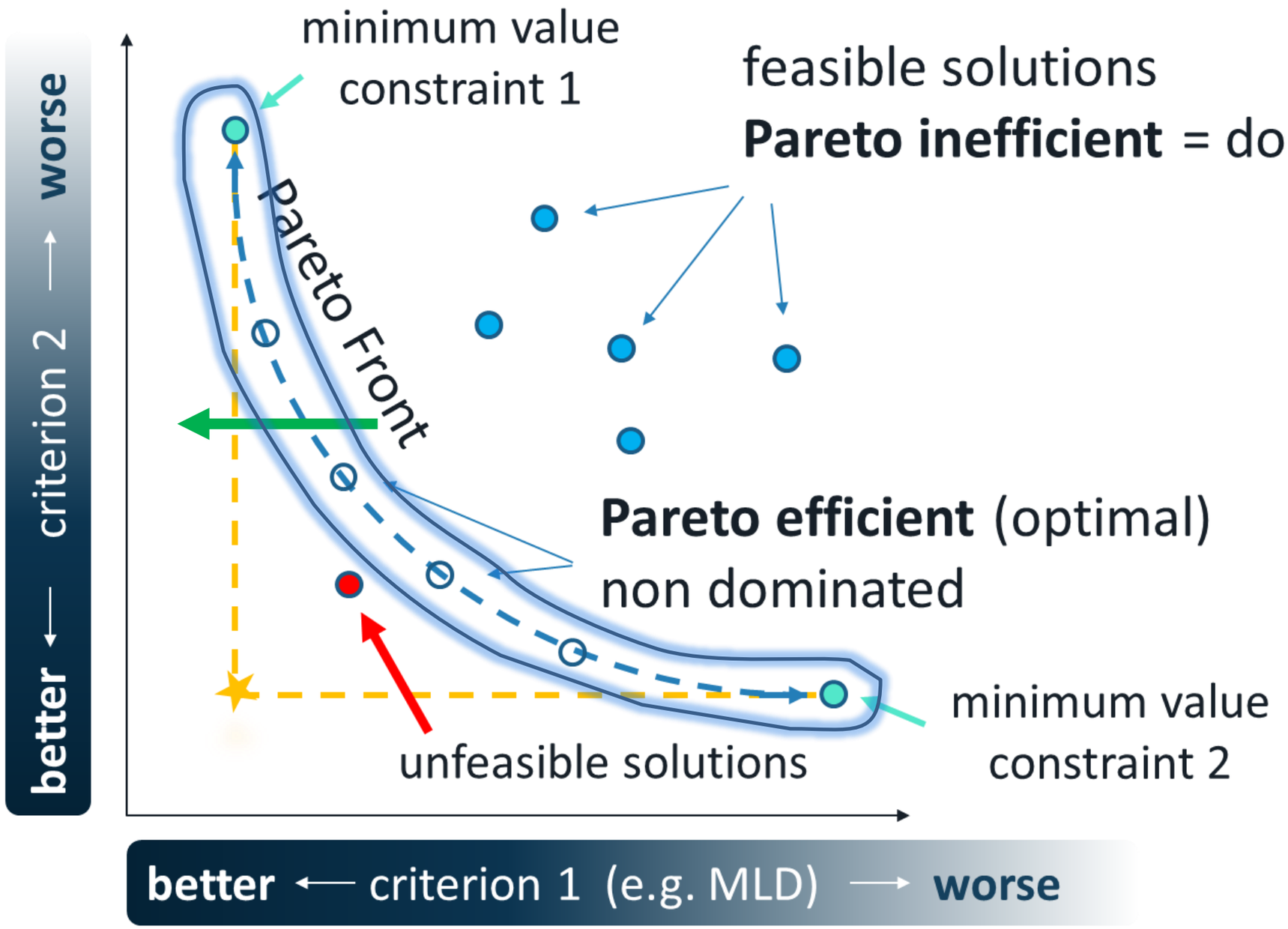
Cilla, Scientific Reports 2020, https://doi.org/10.1038/s41598-019-56966-y

MULTICRITERIA (MULTOBJECTIVE) OPTIMIZATION (MCO)

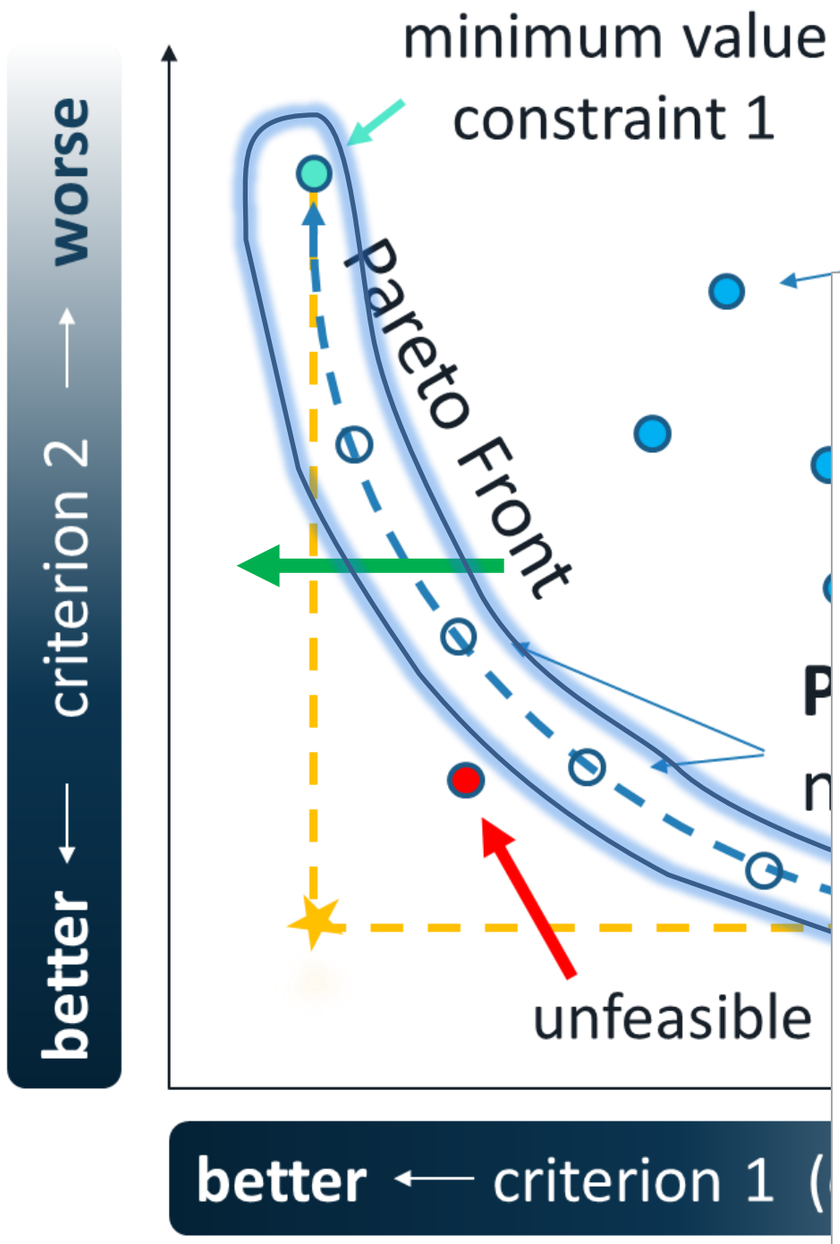
Multi Criteria Optimization (MCO)



Multi Criteria Optimization (MCO)



Multi Criteria Optimization (MCO)



Pareto optimality:

Defines a set of optimal trade-offs between competing objectives

Supports decision-making by selecting the most suitable compromise

a priori and a posteriori MCO

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MCO a posteriori

Idea:

- Algorithms optimize multiple objectives simultaneously (tumor coverage, OAR sparing)

How it works:

- Generates a set of plans showing trade-offs between criteria → user selects the most appropriate.

Advantages:

- Interactive selection of the best compromise
- Greater clinician control over the final plan

Limitations:

- Still requires human input
- Can be time-consuming with many criteria

Possible limitation of a posteriori MCO

- FMO – fluence only (no machine parameters), fast
- DMPO – includes machine parameters (MLC leaf positions, segment weights, etc.) higher computational cost

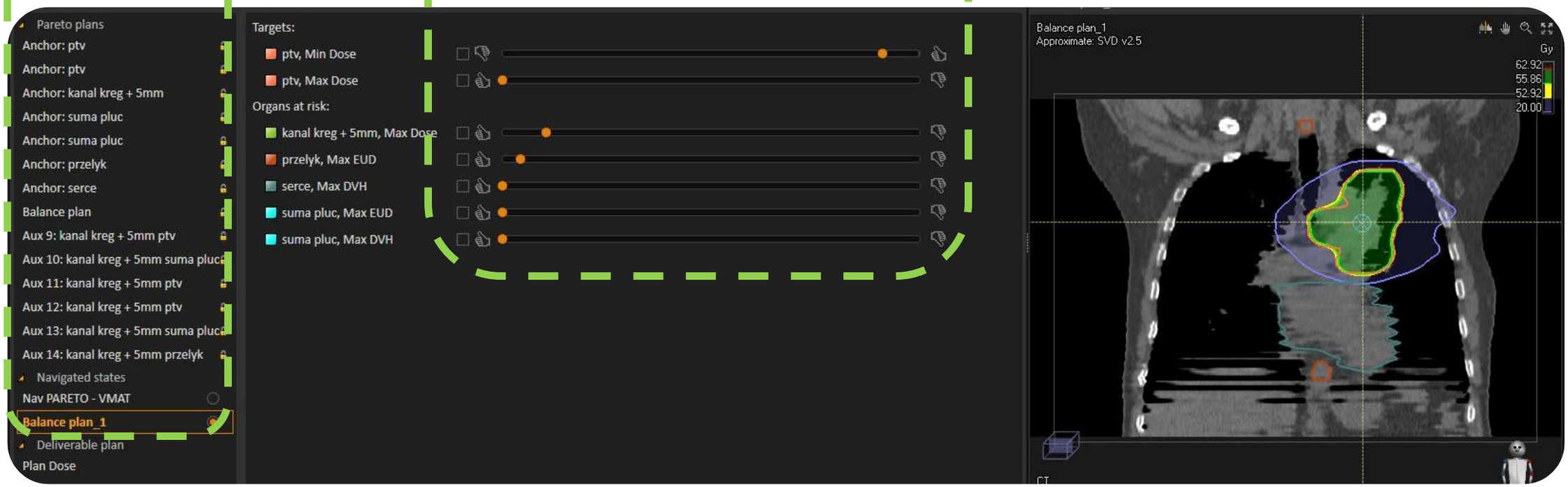
if FMO

- Plans may be near Pareto-optimal in fluence space, not machine parameters
- Deliverable plan created via direct aperture optimization
- Conversion may cause dosimetric discrepancies (McGarry, Kyroudi)
- Usually minor, but can be significant for small targets / low-density tissue → manual fine-tuning may be required

MCO a **posteriori** - RayStation TPS

plans

Interactive Pareto front exploration



- ✓ Define tradeoff objectives (feasible space)
- ✓ Constraints (feasible space)

- ✓ A **posteriori MCO** clinical implementations
- ✓ Navigation-based

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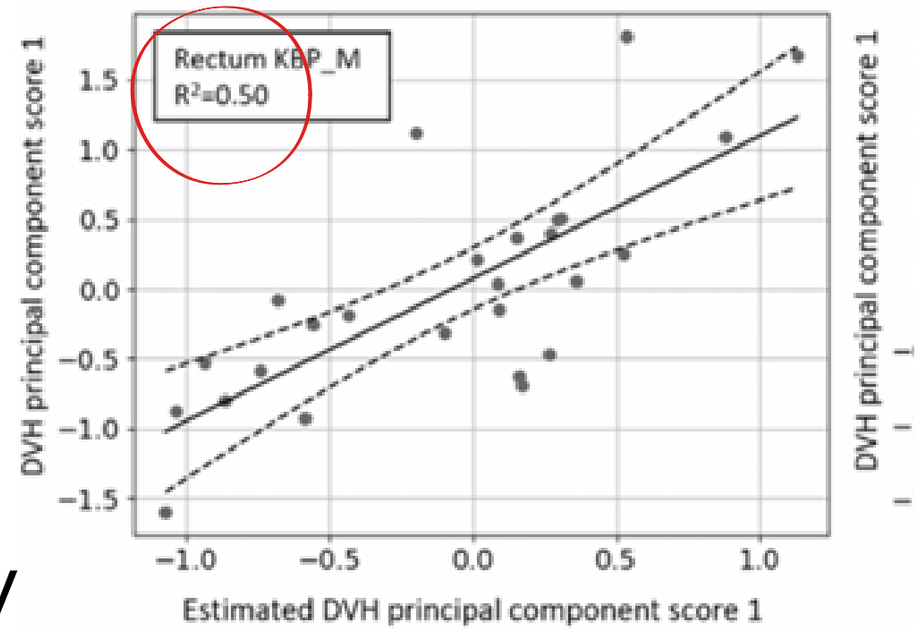
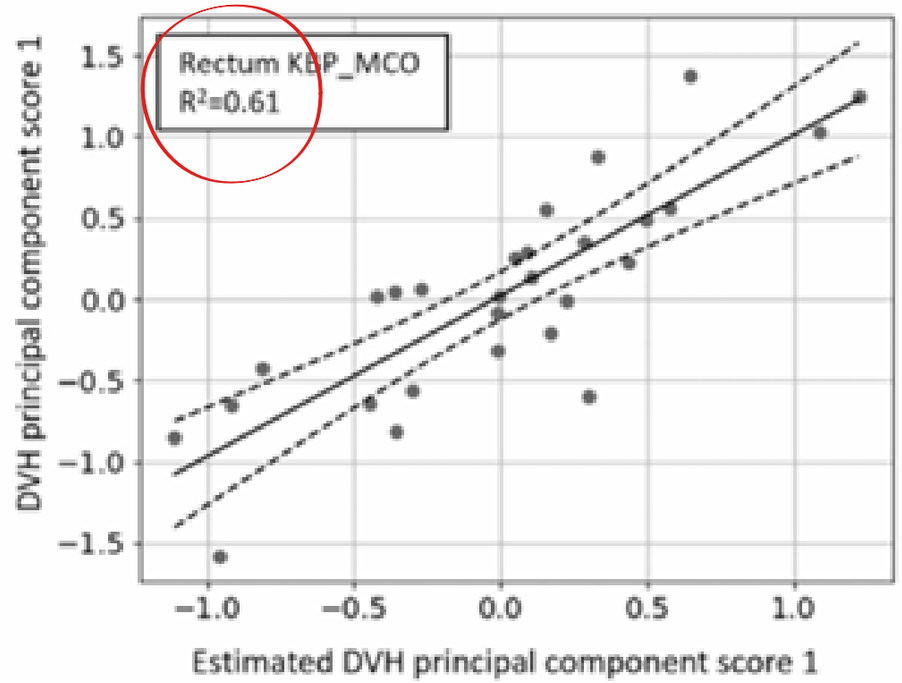
MCO a posteriori - Eclipse TPS

The effect of integrating KBP with MCO in treatment Planning for prostate SBRT





- KBP & MCO → both **improve plan quality** vs. manual
- KBP + MCO → fewer outliers, **better model stats & DVH** predictions, but **no major influence on plan quality**
- **Learning curve** steeper for MCO than KBP
- **MCO integrates directly into planning**, no model training needed
- Both KBP and MCO **shorten planning time** -> KBP achieves greater time reduction
- Large centers → KBP, Small centers → MCO

Jayarathna, J Appl Clin Med Phys. 2023, https://doi.org/10.1002/acm2.13940
Oonsiri *Clin Transl Radiat Oncol*, 2024. https://doi.org/10.1016/j.phro.2024.100595

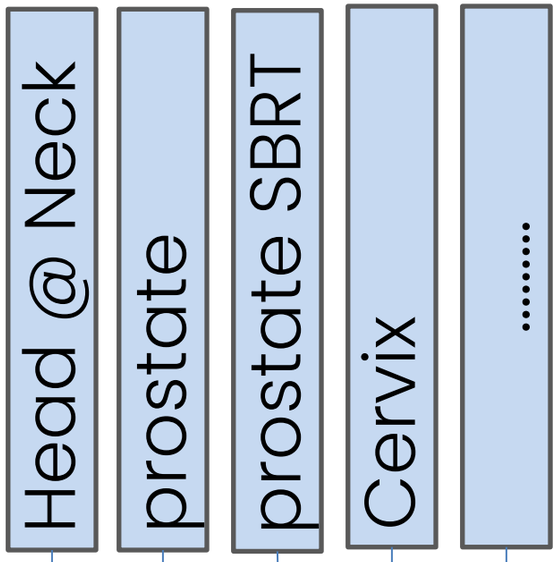
Narodowy Instytut Onkologii

Breedveld S
Heijmen B

MCO a priori Erasmus-iCycle

- iCycle: performs **fully automated beam fluence** and (non-coplanar) beam angle **optimization**
- Acts as a **pre-optimizer** for the TPS (eg. Monaco, Elekta)

tumor site specific wish-lists



- TPS (Monaco): generates a **deliverable segmented plan** that mimics the iCycle dose distribution

commercial TPS:
- Monaco (Elekta linacs)
- Multiplan (Cyberknife)

fully Automated MCO

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MCO a *priori* Erasmus-iCycle – wish-list

Table 1. An example wish-list for automated plan generation with Erasmus-iCycle for localised prostate cancer patients

Constraints				
	Volume	***Type***	***Limit***	
	PTV	Max dose	105% of D_{Px}	
	PTV	Mean dose	101% of D_{Px}	
	Rectum & anus	Max dose	102% of D_{Px}	
	PTV shell 50mm	Max dose	50% of D_{Px}	
	Unspecified tissues	Max dose	105% of D_{Px}	
Objectives				
Priority	***Volume***	***Type***	***Goal***	***Parameters***
1	PTV	↓LTCP	0.8	D_{Px} = 78Gy, α = 0.8
2	Rectum	↓EUD	20Gy	k = 12
3	OAR 2	↓EUD	10Gy	k = 8
4	PTV shell 5mm Skin ring 20mm	↓Max dose ↓Max dose	80% of D_{Px} 20% of D_{Px}	
5	Rectum	↓Mean dose	5Gy	
6	Anus	↓Mean dose	5Gy	
7	Bladder	↓Max dose	5Gy	
8	PTV shell 15mm PTV shell 25mm	↓Max dose	50% of D_{Px} 30% of D_{Px}	
9	Left & right femoral heads	↓Max dose	50% of D_{Px}	

α, cell sensitivity;EUD, equivalent uniform dose;k, volume effect; LTCP, logarithmic tumour control probability; PTV, planning target volume;D_{Px}, prescribed dose.

The priorities assigned to the objectives are used in the *a priori* MCO, guaranteeing for each patient generation of a pareto-optimal plan with clinically favorable balances between all treatment objectives. (Courtesy: A.W. Sharfo).

MCO a priori Erasmus-iCycle – wish-list

Step 1

- Optimize each objective in order of priority
- Reach goal if possible; if not, use best achieved value as constraint
- Move to next objective

Constraints				
	Volume	*Type*	*Limit*	
	PTV	Max dose	105% of D_{Px}	
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	PTV shell 50mm	Max dose	50% of D_{Px}	
	Unspecified tissues	Max dose	105% of D_{Px}	
Objectives				
Priority	***Volume***	***Type***	***Goal***	***Parameters***
1	PTV	↓LTCP	0.8 V_1	D_{Px} = 78Gy, α = 0.8
2	Rectum	↓EUD	20Gy	k = 12
3	OAR 2	↓EUD	10Gy	k = 8
4	PTV shell 5mm Skin ring 20mm	↓Max dose ↓Max dose	80% of D_{Px} 20% of D_{Px}	
5	Rectum	↓Mean dose	5Gy	
6	Anus	↓Mean dose	5Gy	

Plan is generated

Breedveld, 2007, Phys.Med.Biol. 526339-6353

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MCO a priori Erasmus-iCycle – wish-list

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Priority	***Volume***	***Type***	***Goal***	***Parameters***
1	PTV	↓LTCP	0.8 V_1	D_{Px} = 78Gy, α = 0.8
2	Rectum	↓EUD	20Gy V_2	k = 12
3	OAR 2	↓EUD	10Gy	k = 8
4	PTV shell 5mm Skin ring 20mm	↓Max dose ↓Max dose	80% of D_{Px} 20% of D_{Px}	
5	Rectum	↓Mean dose	5Gy	
6	Anus	↓Mean dose	5Gy	

Plan is generated

Breedveld, 2007, Phys.Med.Biol. 526339-6353

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2	Rectum	↓EUD	20Gy V_2	k = 12
3	OAR 2	↓EUD	10Gy V_3	k = 8
4	PTV shell 5mm Skin ring 20mm	↓Max dose ↓Max dose	80% of D_{Px} 20% of D_{Px}	
5	Rectum	↓Mean dose	5Gy	
6	Anus	↓Mean dose	5Gy	

Plan is generated

Breedveld, 2007, Phys.Med.Biol. 526339-6353

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Objectives				
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1	PTV	↓LTCP	0.8 V_1	D_{Px} = 78Gy, α = 0.8
2	Rectum	↓EUD	20Gy V_2	k = 12
3	OAR 2	↓EUD	10Gy V_3	k = 8
4	PTV shell 5mm Skin ring 20mm	↓Max dose ↓Max dose	80% of D_{Px} 20% of D_{Px} V_4	
5	Rectum	↓Mean dose	5Gy	
6	Anus	↓Mean dose	5Gy	

Plan is generated

Breedveld, 2007, Phys.Med.Biol. 526339-6353

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MCO a priori Erasmus-iCycle – wish-list

Step 1

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- Reach goal if possible; if not, use best achieved value as constraint
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Objectives				
Priority	***Volume***	***Type***	***Goal***	***Parameters***
1	PTV	↓LTCP	0.8 V_1	D_{Px} = 78Gy, α = 0.8
2	Rectum	↓EUD	20Gy V_2	k = 12
3	OAR 2	↓EUD	10Gy V_3	k = 8
4	PTV shell 5mm Skin ring 20mm	↓Max dose ↓Max dose	80% of D_{Px} 20% of D_{Px} V_4	
5	Rectum	↓Mean dose	5Gy V_5	
6	Anus	↓Mean dose	5Gy	

Plan is generated

Breedveld, 2007, Phys.Med.Biol. 526339-6353

MCO a priori Erasmus-iCycle – wish-list

Step 1

- Optimize each objective in order of priority
- Reach goal if possible; if not, use best achieved value as constraint
- Move to next objective

Step 2

- Objectives that met goals in Step 1 are further optimized to maximum potential

Constraints				
	Volume	*Type*	*Limit*	
	PTV	Max dose	105% of D_{Px}	
	PTV	Mean dose	101% of D_{Px}	
	Rectum & anus	Max dose	102% of D_{Px}	
	PTV shell 50mm	Max dose	50% of D_{Px}	
	Unspecified tissues	Max dose	105% of D_{Px}	
Objectives				
Priority	***Volume***	***Type***	***Goal***	***Parameters***
1	PTV	↓LTCP	0[illegible]	D_{Px} = 78Gy, α = 0.8
2	Rectum	↓EUD	20[illegible]Gy	k = 12
3	OAR 2	↓EUD	1[illegible]Gy	k = 8

V_1 V_2 V_3

Breedveld, 2007, Phys.Med.Biol. 526339-6353

MCO a priori Erasmus-iCycle – wish-list

Step 1

- Optimize each objective in order of priority
- Reach goal if possible; if not, use best achieved value as constraint
- Move to next objective

Step 2

- Objectives that met goals in Step 1 are further optimized to maximum potential

Constraints				
	Volume	***Type***	***Limit***	
	PTV	Max dose	105% of D_{Px}	
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2	Rectum	↓EUD	20Gy	k = 12
3	OAR 2	↓EUD	10Gy	k = 8

Breedveld, 2007, Phys.Med.Biol. 526339-6353

MCO a priori Erasmus-iCycle – wish-list

iterative tweaking proces

definition of **initial** wish-list

- limited number of training patients (~5)
- automated plan generation with Erasmus iCycle based on **current wish-list**

Plan evaluation

Is it possible to improve plan?

YES

update current wish-list

NO

final wish-list = current wish-list

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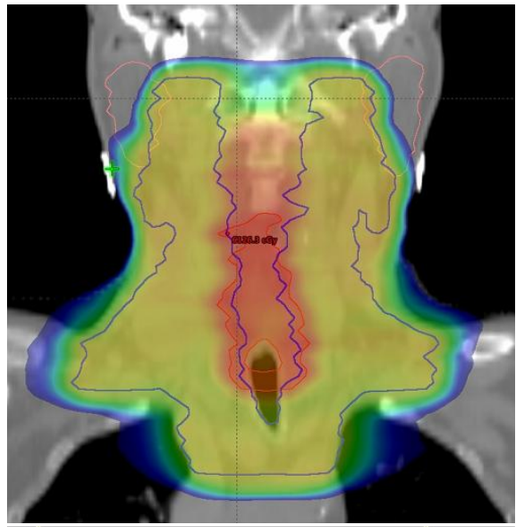
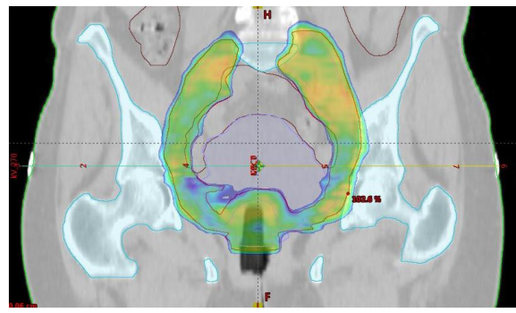
Literature

- **Breedveld S**, Storchi P, Voet P, **Heijmen B**. *iCycle: A novel algorithm for multi-criteria IMRT treatment planning.* (Phys Med Biol, 2012)

- profile optimization for generation of **coplanar and noncoplanar IMRT plans** (Breedveld, Med Phys, 2012)
- **head and neck** (Med Phys, 2012)
- **prostate SBRT** (Phys Med Biol, 2012)
- **IMPT** Treatment (Phys Med Biol, 2013)
- Fully automated MCO Plan Generation (Phys Med Biol 2013)
- **Prostate** (IJROBP, 2014)
- **Robotic Prostate SBRT** (IJROBP, 2015)
- **Cervical** cancer (Radiother Onco, 2015)
- **Spinal metastases** (Radiation Oncology, 2017)
- **HDR brachytherapy** for prostate cancer (Phys Med Biol 2019)
- **MR-Linac** - rectal cancer (Acta Onco, 2020)

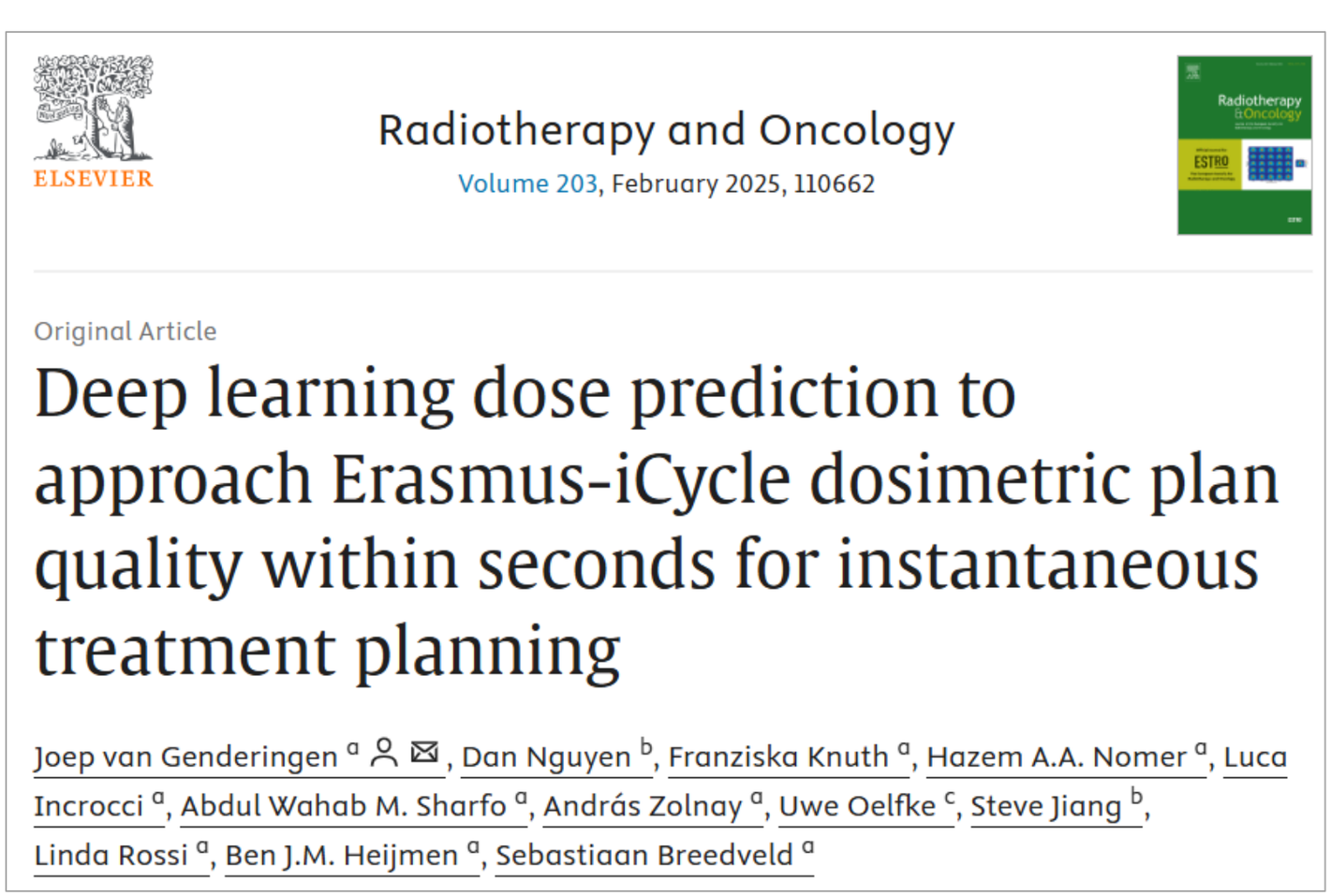




MCO a priori Erasmus-iCycle

- Erasmus-iCycle plans showed better target coverage and sparing of OARs

- *In 97% of cases, automatically generated plans were selected for treatment because of the superior quality* (Phys. Med. Biol 2013)



ELSEVIER

Radiotherapy and Oncology

Volume 203, February 2025, 110662

Original Article

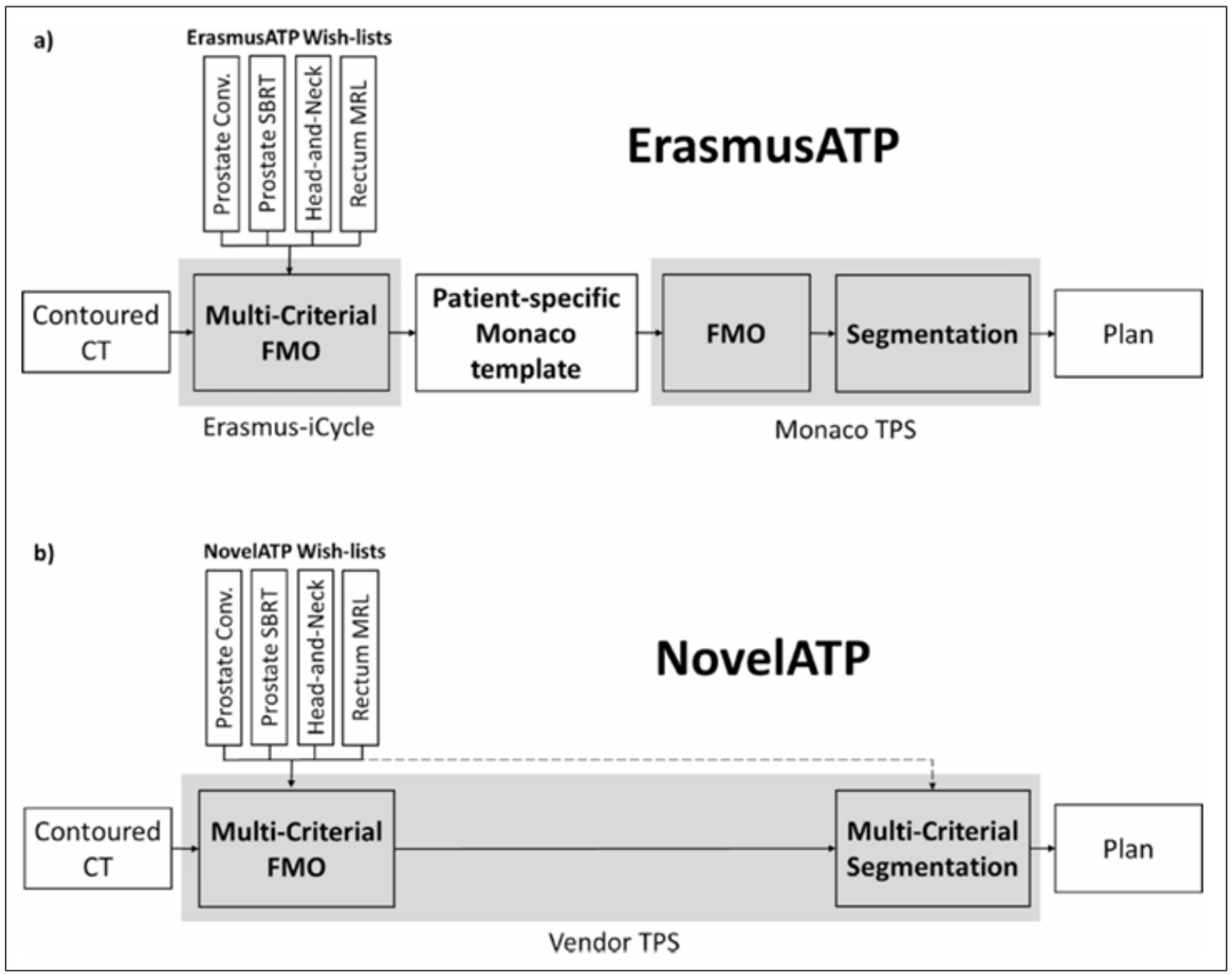
Deep learning dose prediction to approach Erasmus-iCycle dosimetric plan quality within seconds for instantaneous treatment planning

Joep van Genderingen [a], Dan Nguyen [b], Franziska Knuth [a], Hazem A.A. Nomer [a], Luca Incrocci [a], Abdul Wahab M. Sharfo [a], András Zolnay [a], Uwe Oelfke [c], Steve Jiang [b], Linda Rossi [a], Ben J.M. Heijmen [a], Sebastiaan Breedveld [a]

- Developed as an **academic platform**
- Served as a **precursor to MCO and automation**
- Inspired features later adopted in **commercial TPS**

Elekta Monaco Templates

- iCycle concept applied in Monaco
- plan generated with out any human interference (mimicking the Erasmus-iCycle dose distribution)
- the final plan is generated with a CE marked TPS MONACO



NovelATP - new autoplanning application

FMO – fluence map optimization

Bijman, Radiotherapy and Oncology 2021, https://doi.org/10.1016/j.radonc.2021.03.003

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Elekta Monaco Templates

MCO FMO – ErasmusATP vs. NovelATP

1. Both are **wish-list driven** & conceptually similar

2. Differ in implementation:

- NovelATP uses **new code, solver, patient model**
- **Wish-list cost functions** differ between systems
- **Segmentation of FMO plans**
  - ErasmusATP → wish-list only in FMO
  - NovelATP → wish-list in FMO & segmentation

Bijman, Radiotherapy and Oncology 2021, **https://doi.org/10.1016/j.radonc.2021.03.003**

ART

Narodowy Instytut Onkologii

Adaptive Radiotherapy (ART) with Automation

1. **Off-line**
   Previously discuses solutions

2. **On-line (oART)**
   New tools

Idea

- Daily plan modification based on **patient anatomy changes**

Automation Supports

- **Fast re-planning**
- **Auto-contouring** of organs
- **Auto-plan generation** per clinical criteria

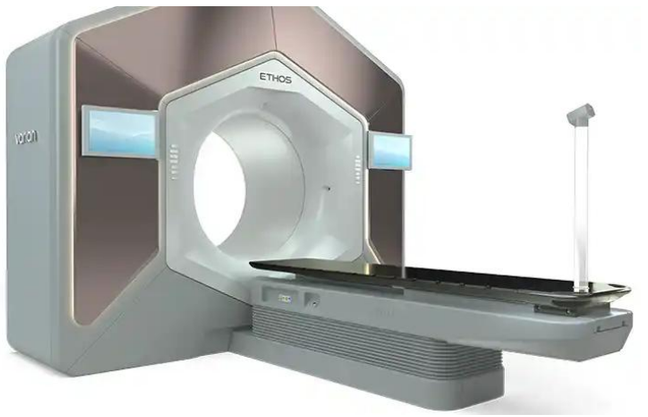
Significance

- Enables **real-time personalized treatment**

Commercial On-Couch Adaptive RT Systems

1. **Varian Ethos**
   - CBCT-based oART platform
   - Integrated AI contouring & auto-planning

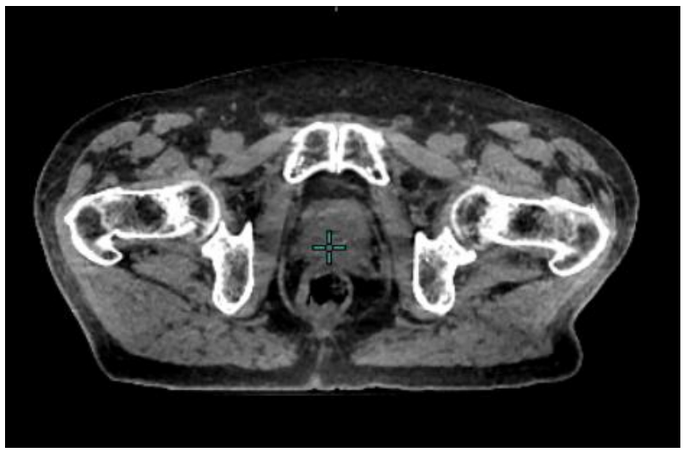
2. **Elekta Unity (MR-Linac)**
   - MRI guidance + daily plan adaptation
   - Real-time soft tissue visualization



3. **Elekta Evo (CT-Linac)**
   - AI-enhanced CT imaging
   - Adaptive workflows for Elekta
4. **Accuray Radixact + Cenos**
   - Online adaptive solution (pending FDA)
   - Supports re-planning with daily kVCT
5. **Accuray Radixact with ClearRT**
   - Daily kVCT imaging for plan adaptation
   - Synchrony® for motion adaptation

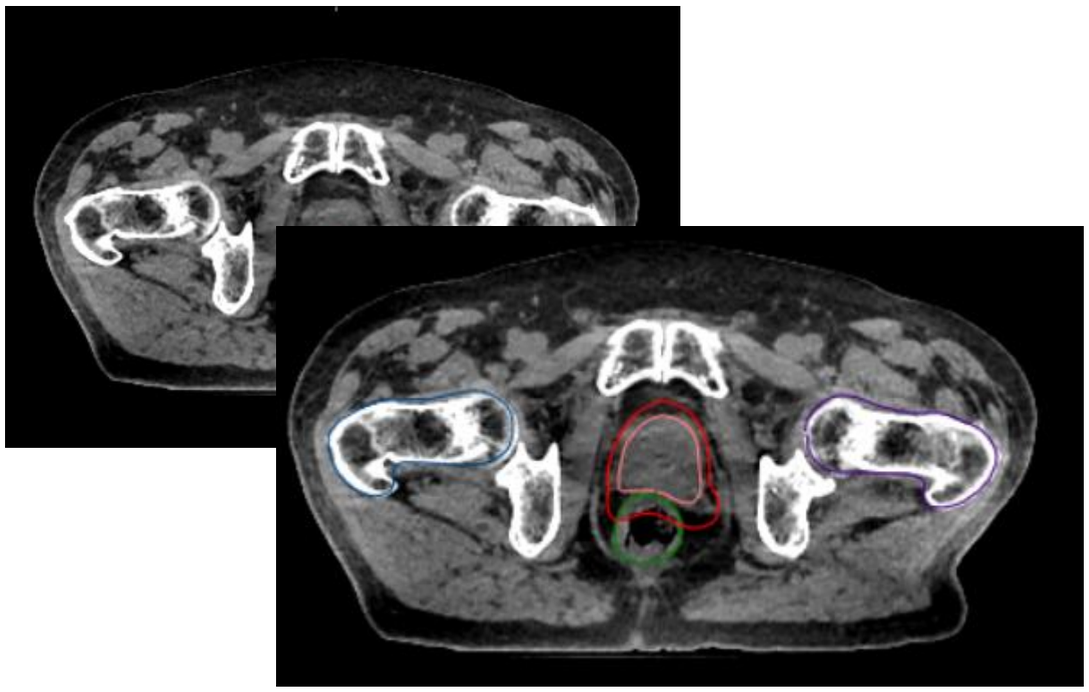
oART – Example: Varian Ethos

- Daily CBCT → captures patient's current anatomy
- Rigid & deformable registration with reference CT



oART – Example: Varian Ethos

- Daily CBCT → captures patient's current anatomy
- **Rigid & deformable registration** with reference CT
- **AI auto-contouring** of targets & OARs → manual edits if needed
- **Synthetic CT** generation (no longer in use since Ethos v2.0)



Anatomical region	Anatomical site includes at least one of theses structures	AI segmentation model	Influencer structures created via AI segmentation
Pelvis	Prostate	Prostate	Prostate, rectum, bladder, bowel, seminal vesicles
Pelvis	Uterus	Cervix	Uterus, rectum, bladder, bowel
Pelvis	Bladder, rectum	Unisex pelvis	Rectum, bladder, bowel
Abdomen	Pancreas, duodenum, liver, stomach	Unisex abdomen	Duodenum, pancreas, liver, stomach
Other	AI segmentation is not available.		

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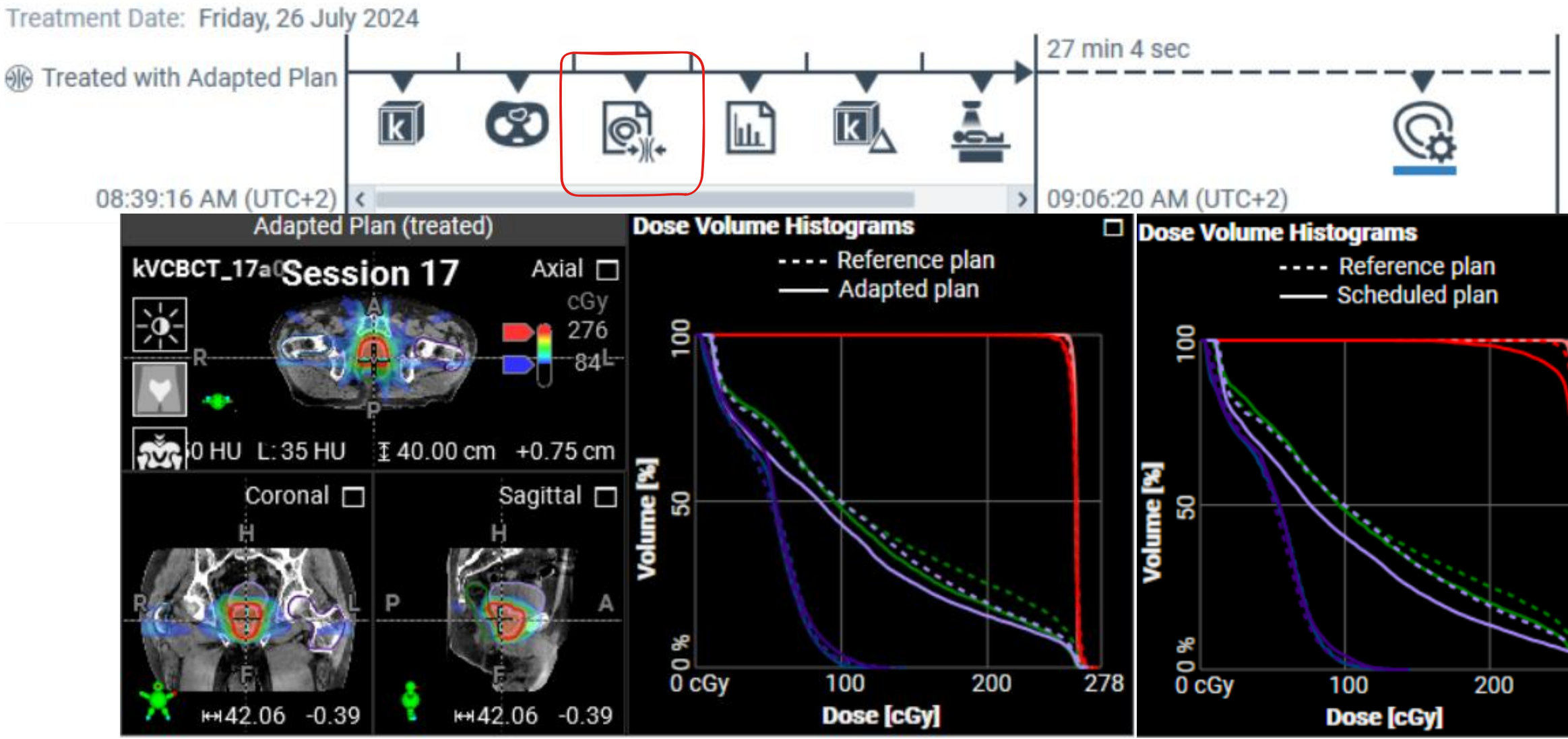
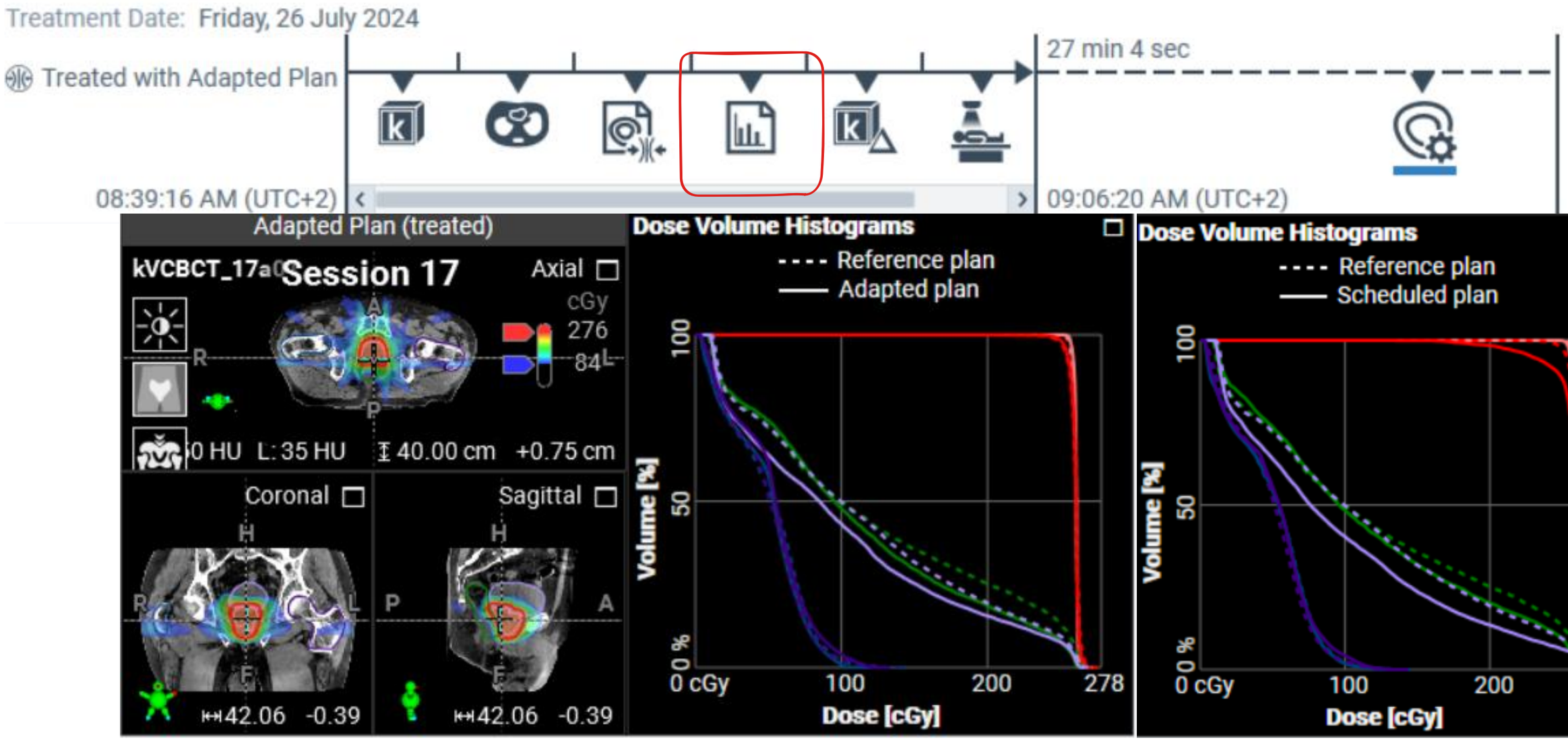
oART – Example: Varian Ethos

- Automated re-planning using predefined clinical goals
- Plan selection → scheduled vs adapted



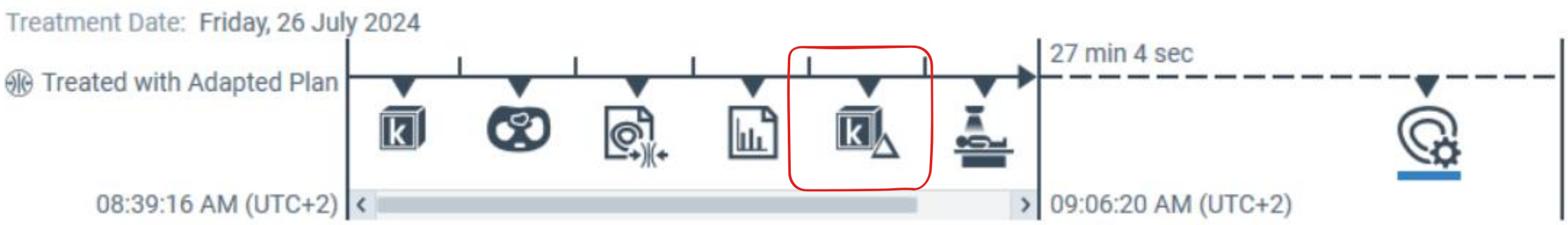
oART – Example: Varian Ethos

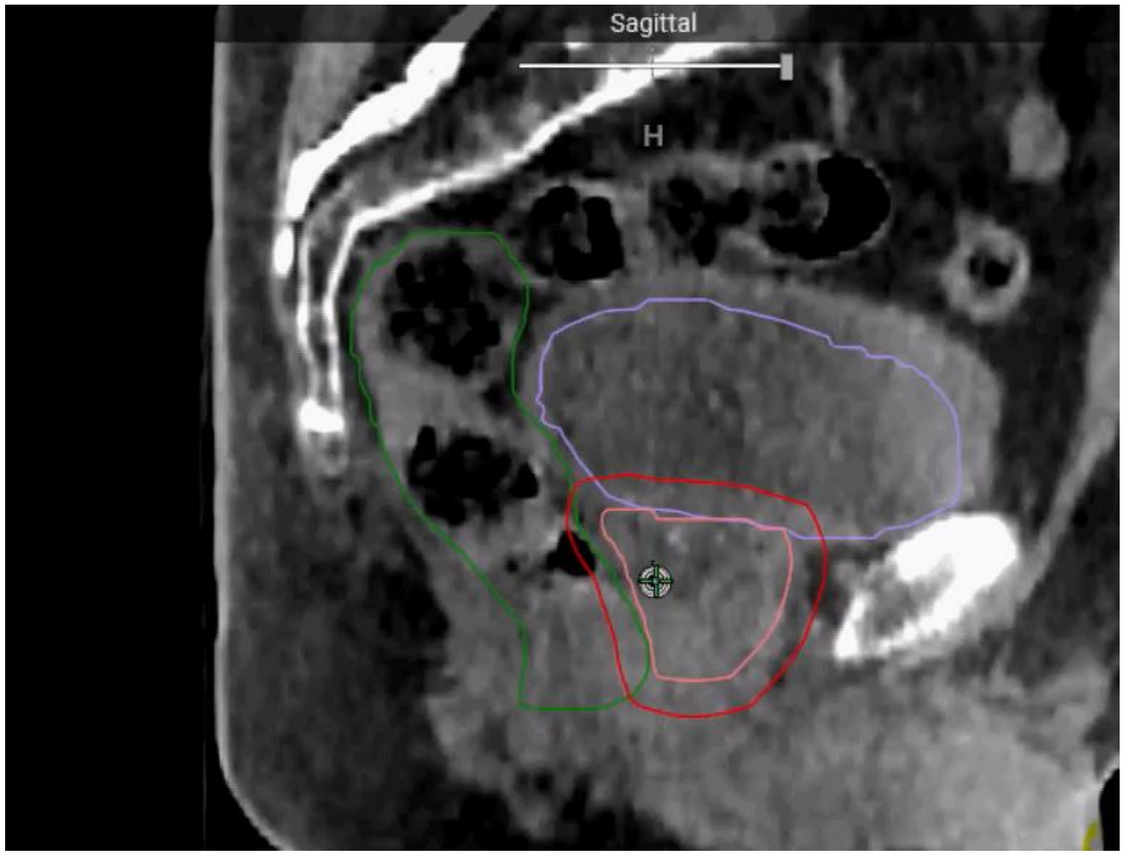
- Automated **re-planning** using predefined clinical goals
- Plan selection → **scheduled** vs **adapted**
- Plan QA & **approval** done while patient is on couch

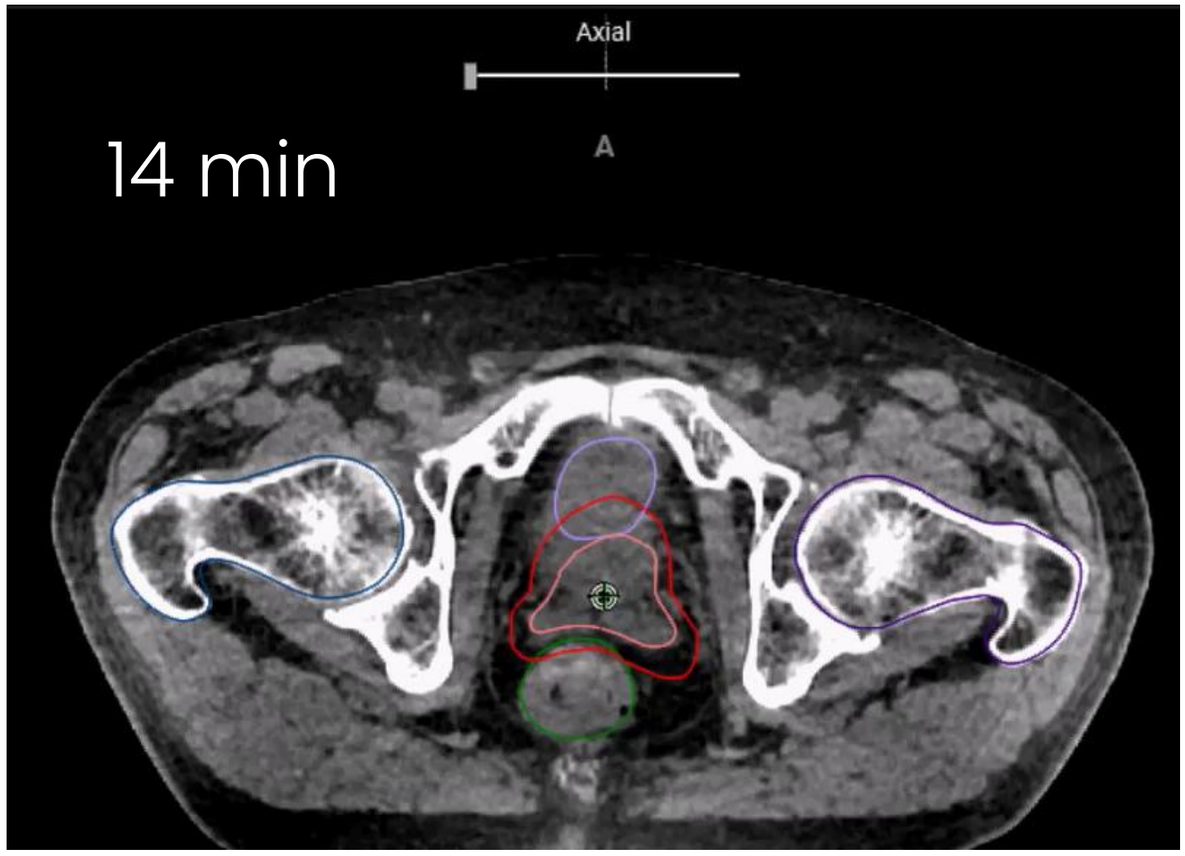


oART – Example: Varian Ethos

- Optional verification CBCT before treatment delivery







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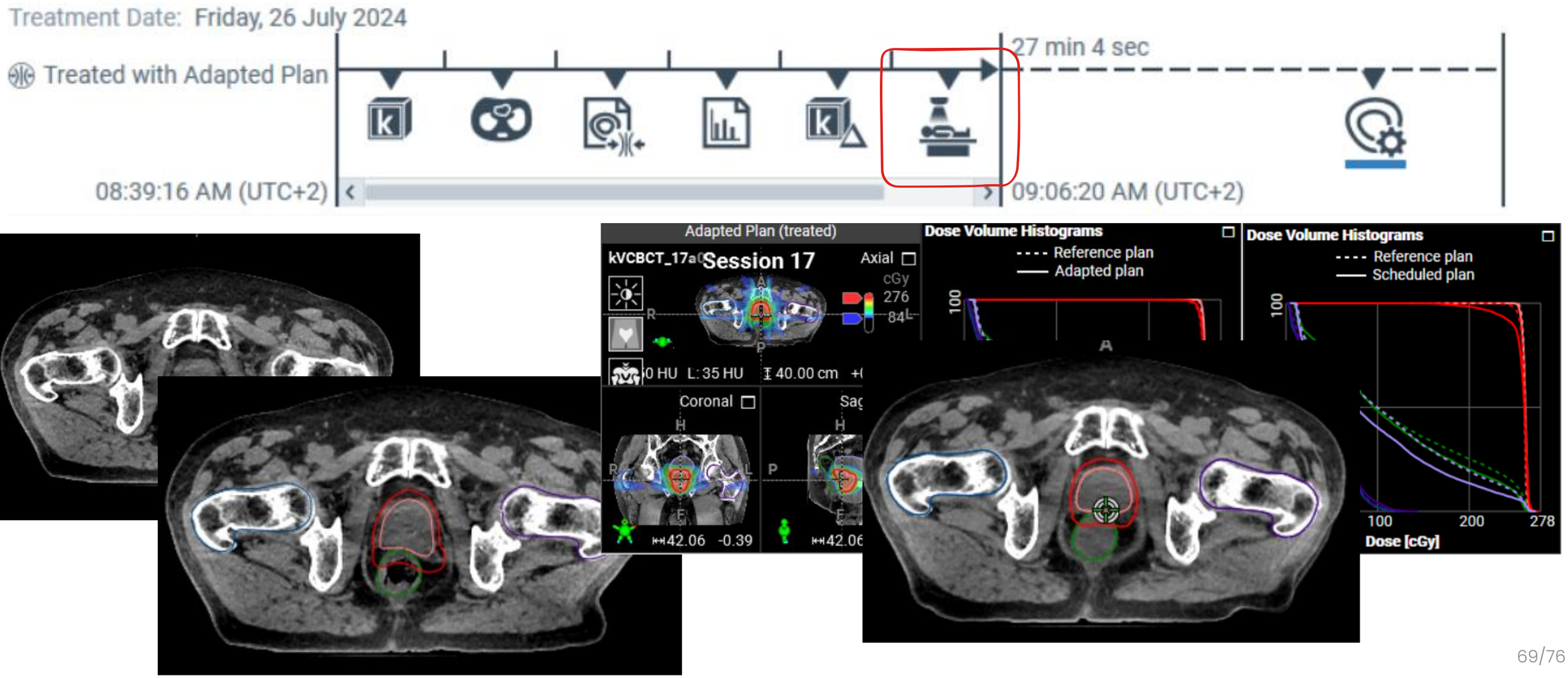
oART – Example: Varian Ethos

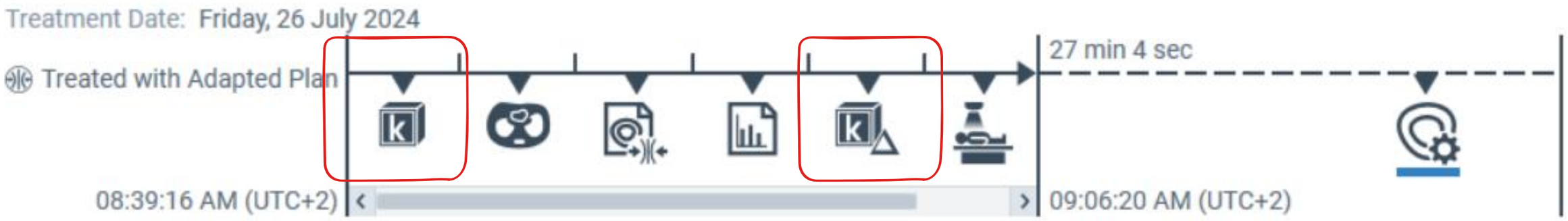
- **Treatment delivery** with adapted plan in the same session

Lack of table rotations, breathing control, SGRT



oART – sesion time

	time [min:s] average ± SD
all tumor sites	20:00 ± 09:10
prostate	12:50 ± 03:30
gynecology	26:20 ± 08:00
bladder	13:00 ± 04:00



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Auto-Planning Systems

- **Philips Pinnacle Auto-Planning** – template-based optimization
- **RayStation Auto-Planning** – scripting + automated optimization
- **Elekta Monaco Templates** – MCO, template-based optimization
- **Academic iCycle** – fully automated MCO pre-optimizer, integrated with Monaco
- **Varian Ethos** – scripting + KBP, adaptive auto-planning

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Automation in TPS
Varian vs Elekta vs Philips vs RaySearch

TPS	Key Automation Module	API	Strengths	Limitations
Elekta Monaco Unity	Monaco Auto-Planning Unity MR-Linac (online ART)	Monaco Script API (limited)	Biological optimization, MR integration, real-time ART	Less open API, complex configuration
Philips Pinnacle	Auto-Planning (template-based)	Python	Simplicity, automatic templates, extensive clinical experience	Development limited
RaySearch RayStation	RS Scripting API Auto-Planning MCO	Python	Flexibility, easy AI/ML integration, strong community	Needs strong clinical validation, less widespread than Eclipse
Varian Eclipse	ESAPI RapidPlan	C#	Large clinical base ARIA integration	Closed ecosystem
Varian ETHOS	online ART	-		

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Why automation?

Advantages of automation

- Increased **efficiency & consistency**
- Reduced **inter-planner variability**
- Fewer **errors**
- Supports **Adaptive Radiotherapy (ART)**

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Why automation?

Potential Risks of automation

Human related

1. Reduced oversight → less clinical attention
2. Errors from Over-Reliance (Automation Bias) → blind trust without expert verification

System related

3. Bias in training data (AI/KBP) → incorrect or inadequate plans
4. Validation & QA Challenges
5. Lack of Transparency (Black Box AI)
6. System Errors & Error Propagation

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Why automation?

Potential Risks of automation

Future

7. Loss of individualization → overly generic, less patient-specific plans
   Unusual anatomy / rare tumors → risk of poorer plans
8. Skill degradation → reduced manual expertise among planners.
   All current implementations of automated planning require a high-level of manual planning knowledge for configuration.
9. Technical failures / bugs → delays or incorrect plans
10. Legal & ethical issues → unclear responsibility (system vs. clinician)

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Summary

- Automation evolved from rule-based methods to AI-driven solutions
- KBP, MCO, Auto-Planning, and oART improve plan quality, efficiency, and consistency
- Commercial systems (Eclipse, RayStation, Pinnacle, Monaco, Ethos, Unity, Evo, Cenos) provide diverse automation pathways
- Benefits: reduced variability, knowledge sharing, faster workflows, real-time personalization
- Challenges: data quality, transparency, validation, maintaining clinical oversight
- **Future:** deeper AI integration → fully personalized, adaptive Treatment with one mouse klick

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Thank you

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