Generative AI helps Radiotherapy Planning with User Preference (DEMO)

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Paper link:

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Motivation: Background and Challenges in RT Planning

RT Planning Background:

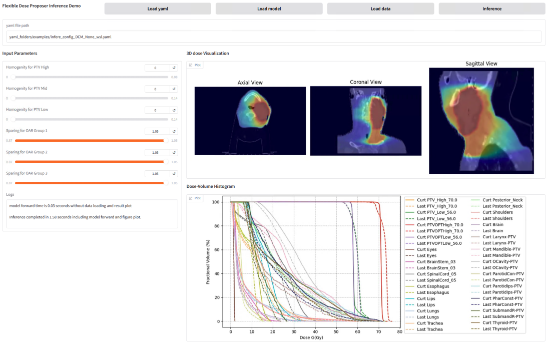
- Radiotherapy (RT) is one of the most common cancer treatments (suitable for about 50% cancer patients)
- RT planning is complex and time-consuming
- RT planning involves a multidisciplinary team and can be subjective

Current Limitations:

- RT planning varies significantly across institutions
- Existing models lack user interaction to balance PTV/OAR trade-offs
- RapidPlan™ is DVH-based, missing spatial dose details
- RapidPlan requires institution-specific models

Our Solution:

- Interactive AI dose prediction
- User-defined preferences via sliders
- Integration in treatment planning system



Key Metrics:

- Homogeneity Index (HI):

$$\mathrm{HI} = \frac{D_{05} - D_{95}}{D_{50}}$$

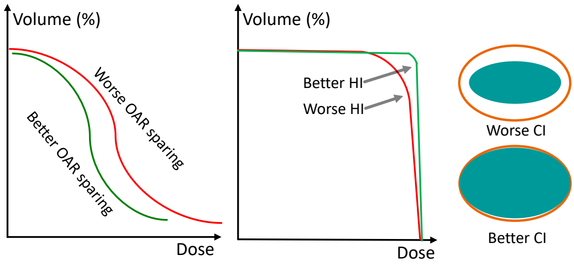
- Conformity Index (CI):

$$\mathrm{CI} = \frac{V_{\text{covered}}}{V_{\text{PTV}}}$$

- OAR Sparing: Mean doses to organs at risk

The Trade-off:

- Better PTV homogeneity **or** Better OAR sparing
- Different planners have different preferences
- Traditional models cannot adapt



Innovation:

Pioneering dose prediction model with interactive sliders enabling real-time customization of trade-offs

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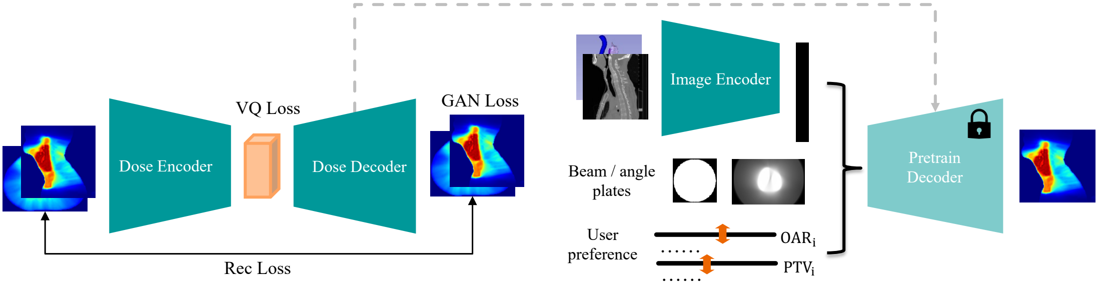

(a) Stage 1: Decoder Pretraining (b) Stage 2: Flexible Dose Prediction

Stage I: Foundational Decoder

- VQ-VAE architecture
- Pre-trained on 31K doses
- Stabilizes training with realistic dose distributions

Stage II: Flexible Prediction

- Multi-conditional inputs (CT, structures, preferences)
- random sampling for preferences during training
- One-step generation via GANs (fast inference)

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Stage I: Foundational Decoder

$$\mathcal{L}_{\text{stage1}} = \underbrace{\mathbb{E}_i[\|x_i - \hat{x}_i\|]}_{\text{Reconstruction}} + \beta L_{vq} + L_{adv}(x, \hat{x}) + \underbrace{\lambda \cdot \log\left(\mathbb{E}_{i<j}\left[\exp(-t\|\hat{z}_i - \hat{z}_j\|^2)\right]\right)}_{\text{Uniformity}}$$

Stage II: Flexible Prediction

$$\mathcal{L}^{(i)}_{\text{stage2}} = \underbrace{\|x_i - \hat{x}_i\|}_{\text{Image Recon.}} + \underbrace{\|z_i - \hat{z}_i\|}_{\text{Latent Recon.}} + L_{adv}(x_i, \hat{x}_i) + \mathcal{L}^{(i)}_{\text{obj}}$$

$$\mathcal{L}^{(i)}_{\text{obj}} = \underbrace{\|\tilde{h} - \hat{h}\|}_{\text{ptv HI preference}} + \underbrace{\|p - \hat{p}\|}_{\text{ptv dose alignment}} + \underbrace{\|\tilde{w} \cdot u_{\text{oar}} - \hat{u}_{\text{oar}}\|}_{\text{oar-sparing preference}}$$

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Dataset:

- 6 cohorts of head-and-neck cancer
- Total: 820 training, 103 validation, 113 test cases
- Stage I pre-trained on 31K doses

Data Distribution:

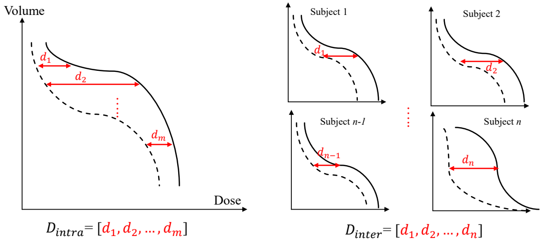
Cohort	0	1	2	3	4	5
Train	370	147	128	103	52	20
Valid	48	17	15	14	8	1
Test	54	19	17	12	7	4

Baseline:

- Varian RapidPlan™ (high-quality model)
- All test data followed RapidPlan requirements

Evaluation Metrics:

- **DVH Estimation Accuracy:** Expected vs. achieved DVH differences
- **Inter-patient** and **Inter-patient** highlight different perspectives
- Quality of deliverable plans



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Intra-patient Differences:

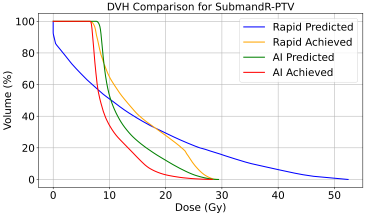
- **15/15** OARs: FDP outperforms RapidPlan
- (check tables in manuscript)

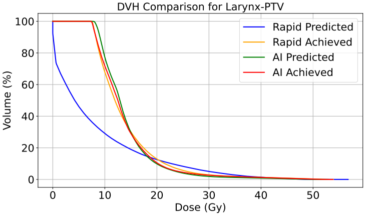
Inter-patient Differences:

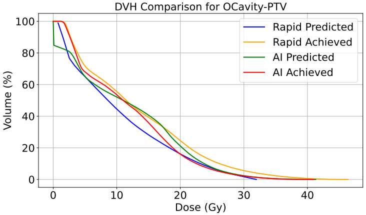
- **12/15** OARs: FDP shows lower variability
- (check tables in manuscript)

Key Insight:

FDP provides more robust and reliable DVH estimations







Some examples about expected vs. achieved DVHs for RapidPlan and our FDP model

Results: Structure-wise Plan Quality Comparison

Table: Percentages of better, worse, similar when compare the FDP to RapidPlan (per structure)

OAR	SpinalCor 05	Larynx-PTV	Lips	Mandible-PTV	OCavity-PTV	ParotidCon-PTV	ParotidIps-PTV	Esophagus
better	47.50	30.00	47.50	31.25	64.56	32.50	48.68	30.23
worse	5.00	21.43	0.00	1.25	1.27	6.25	5.26	4.65
similar	47.50	48.57	52.50	67.50	34.18	61.25	46.05	65.12

OAR	SubmandL-PTV	Shoulders	SubmandR-PTV	Posterior Neck	PharConst-PTV	BrainStem 03	Trachea	**OAR count**
better	59.57	0.00	71.11	12.50	56.16	7.50	51.16	**14**
worse	2.13	0.00	6.67	6.25	2.74	3.75	0.00	**0**
similar	38.30	100.00	22.22	81.25	41.10	88.75	48.84	-

PTV	HI (PTVHigh)	CI (PTVHigh)	HI (PTVMid)	CI (PTVMid)	HI (PTVLow)	CI (PTVLow)	**PTV count**
better	0.00	0.00	0.00	4.00	1.43	4.29	**1**
worse	0.00	0.00	0.00	4.00	0.00	4.29	**0**
similar	100.00	100.00	100.00	92.00	98.57	91.43	-

Thresholds: 1 Gy for OARs; 0.015 for PTV indices (HI & CI). **bold** *= category counts.*

Summary: OAR: 14 better / 0 worse PTV: 1 better / 0 worse

Results: Clinical Integration and Deliverable Plans

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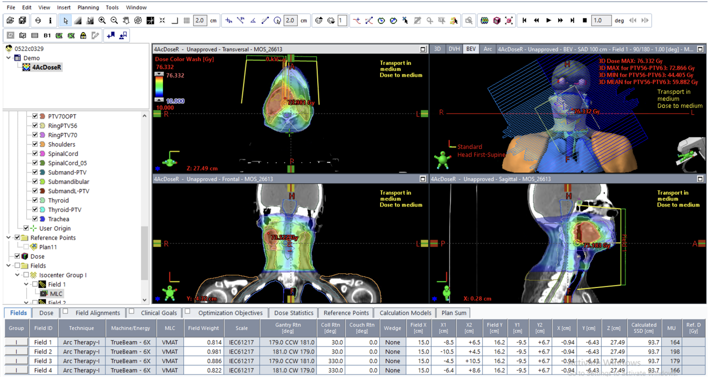
Top OAR Improvements:

- SubmandR-PTV: **71%** better
- OCavity-PTV: **65%** better
- SubmandL-PTV: **60%** better

Clinical Significance:

- Reduced toxicity for patients
- Maintained PTV coverage
- Better quality of life outcomes

Eclipse Treatment Planning System Integration



FDP predictions are optimized in Eclipse to generate deliverable clinical plans

Key Takeaway

FDP delivers superior quality plans in Eclipse treatment planning system.

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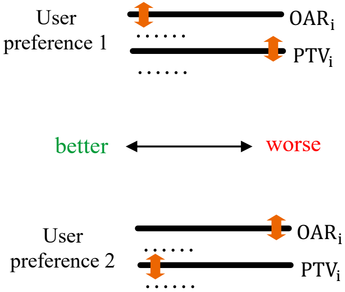

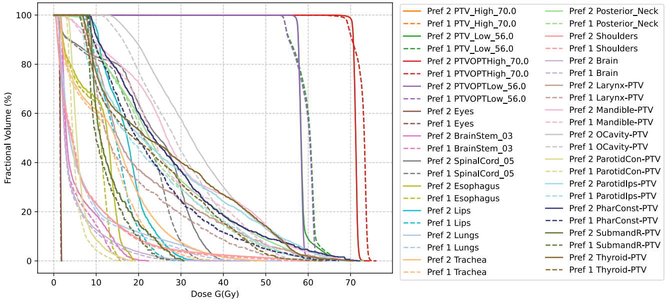

Preference 1 (P1): OAR-focused

- Prioritize OAR sparing
- Accept higher PTV dose heterogeneity
- Lower OAR mean/max doses

Preference 2 (P2): PTV-focused

- Prioritize PTV homogeneity
- Accept higher OAR doses
- Better PTV dose distribution

Real-time adaptation: Model responds to slider adjustments within seconds

Key Contributions:

1. Novel two-stage framework with foundational decoder
2. First interactive dose prediction model with real-time user preference sliders.
3. Clinical integration with treatment planning systems
4. Superior performance vs. RapidPlan

Limitations:

- Currently focused on head-and-neck cancer
- clinical validation is limited

Future Directions:

- Extend to other cancer treatment sites
- More rigorous clinical validation
- Integration with automated planning pipelines
- Explore diffusion-based alternatives

Impact

Significant step toward personalized AI-assisted radiotherapy planning

Demo Video:

https://huggingface.co/Jungle15/DoseProposerDemo

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Thank You!

Questions?

Contact: riqiang.gao@siemens-healthineers.com

Demo Video:

Paper: