

# Practice Impact and next steps

## Omics & AI for MRLinac

Department of Radiation Oncology, University Hospital, LMU Munich  
24.11.22 | PD Dr. Stefanie Corradini

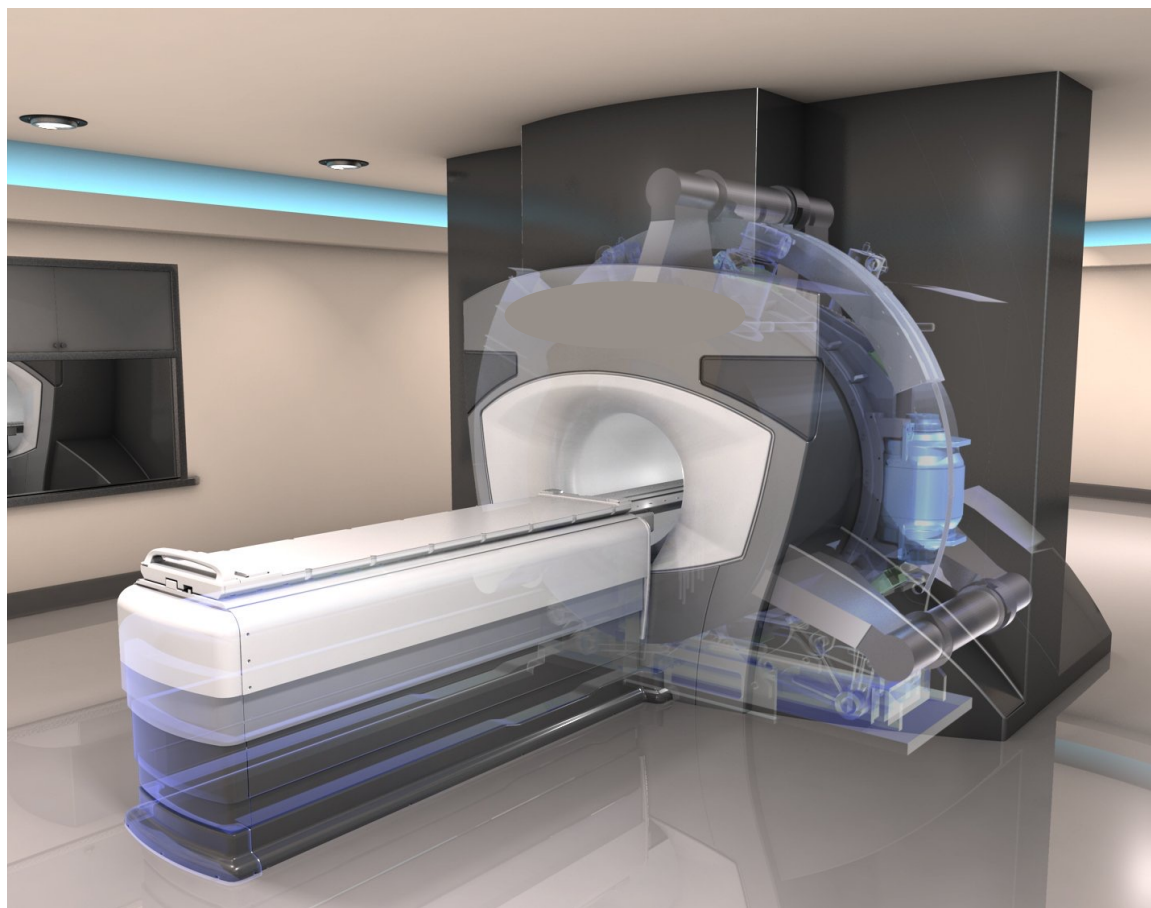


# Global Disclaimer

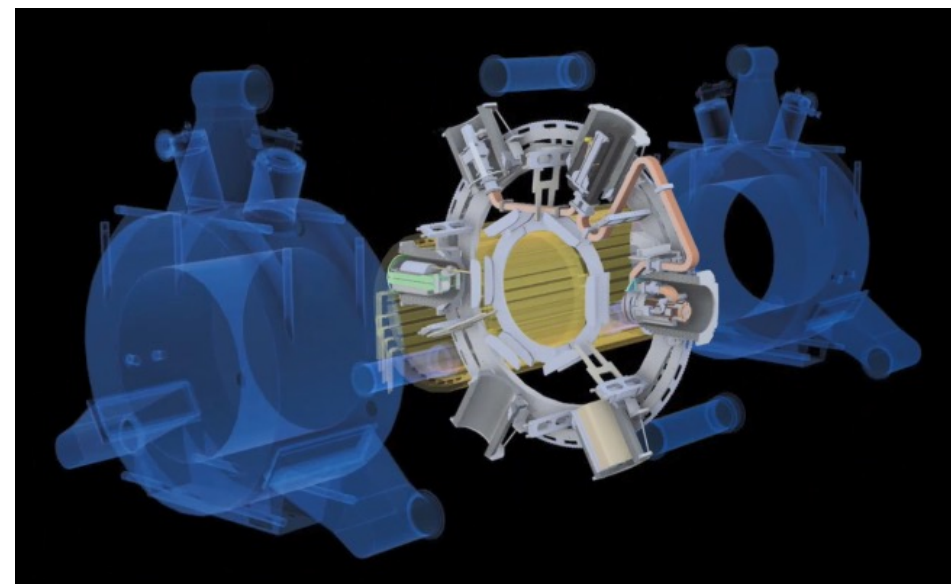


- In keeping with our role as a university hospital, we are active in research and receive funding from various sources
- Research is supported by government agencies: Free State of Bavaria, Cancer Aid, DFG, BMBF (DKTK, DZL) and BMU
- For individual research projects and/or meeting presentations and participation in advisory boards, the department is supported by:  
 AstraZeneca, MERCK, MSD, BMS, ViewRay, ELEKTA, Brainlab and C-RAD and OPASCA

# MRgRT MRIdian

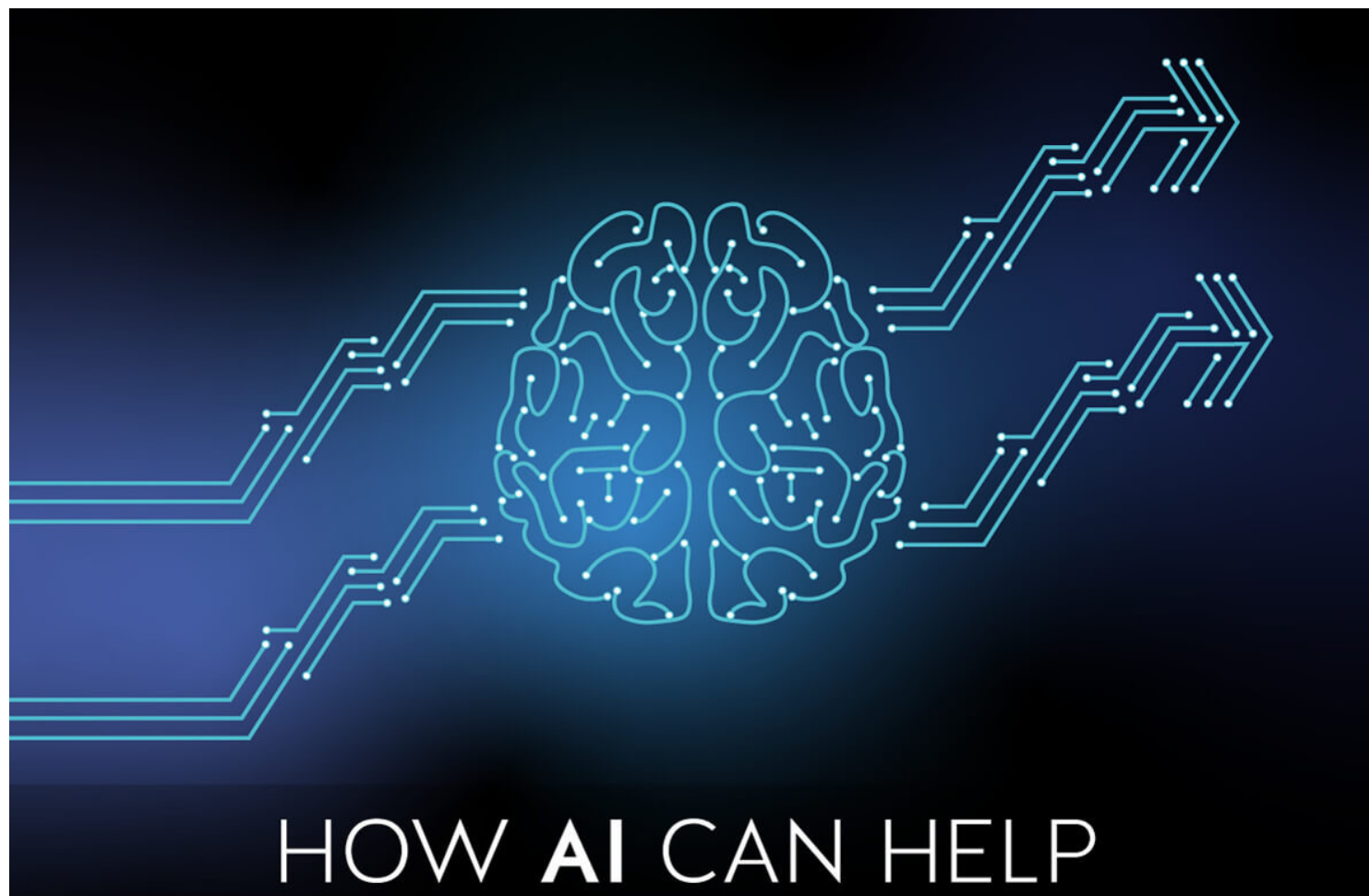


- **New Technology: Hybrid MR-Linac Systems**
- **5 active Sites in Germany**



AI

MRLinac



# AI in MRgRT

## Challenges

### Challenges for providers:

- MRI environment → not all patients are suitable
- Adaptive workflows
- Close interdisciplinary teamwork required
- Longer treatment times
- High costs



# AI in MRgRT

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- **Adaptive workflows**
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Original Article

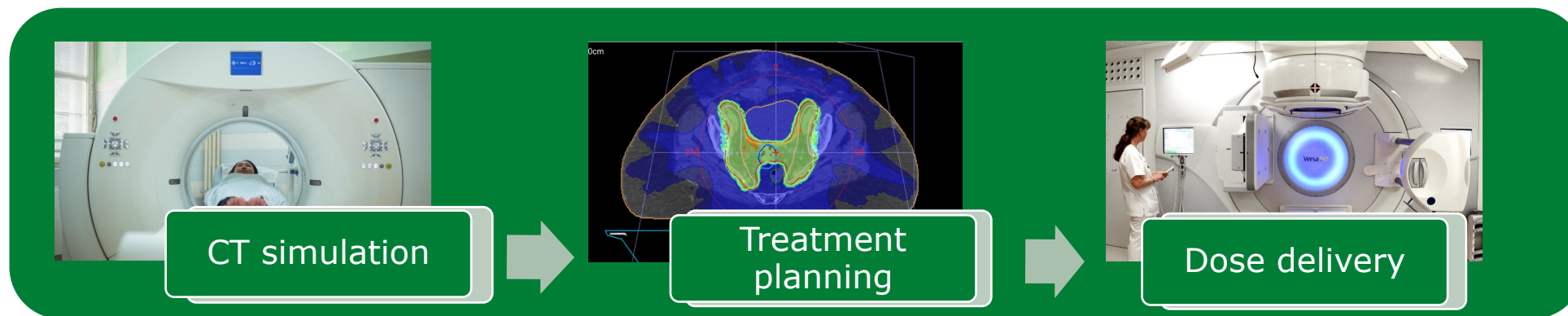
ESTRO-ACROP recommendations on the clinical implementation of hybrid MR-linac systems in radiation oncology



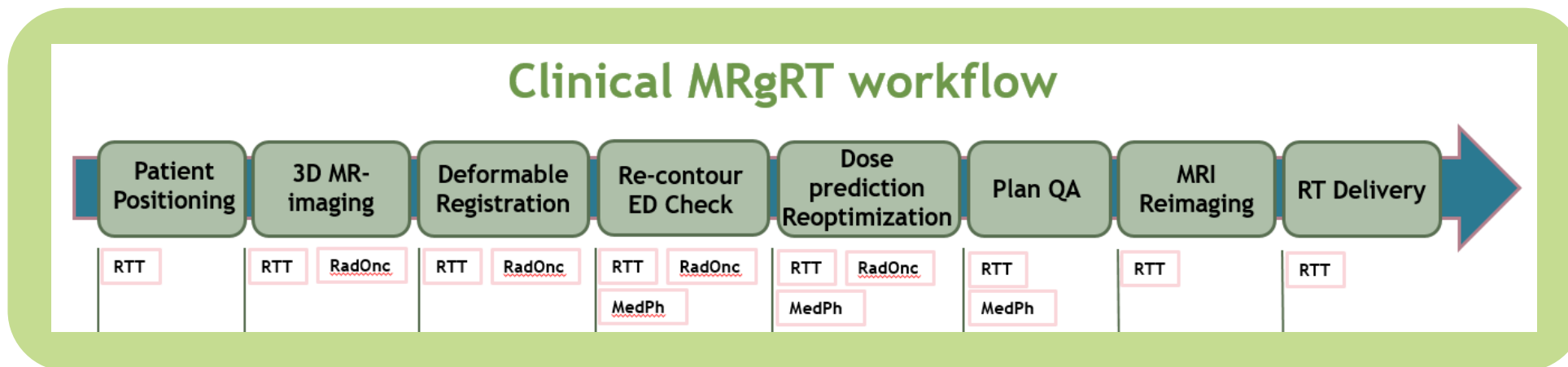
Stefanie Corradini <sup>a,\*</sup>, Filippo Alongi <sup>b</sup>, Nicolaus Andratschke <sup>c</sup>, David Azria <sup>d</sup>, Omar Bohoudi <sup>e</sup>, Luca Boldrini <sup>f</sup>, Anna Bruynzeel <sup>e</sup>, Juliane Hörner-Rieber <sup>g</sup>, Ina Jürgenliemk-Schulz <sup>h</sup>, Frank Lagerwaard <sup>e</sup>, Helen McNair <sup>i</sup>, Bas Raaymakers <sup>h</sup>, Tine Schytte <sup>j</sup>, Alison Tree <sup>i</sup>, Vincenzo Valentini <sup>f</sup>, Lotte Wilke <sup>e</sup>, Daniel Zips <sup>k</sup>, Claus Belka <sup>a</sup>

# AI in MRgRT Workflows

CT



MRI





# AI in MRgRT

## Patient acceptance

First prospective clinical evaluation of feasibility and patient acceptance of magnetic resonance-guided radiotherapy in Germany

Sebastian Klüter<sup>1,2,3</sup> · Sonja Katayama<sup>1,2,3</sup> · C. Katharina Spindeldreier<sup>1,2,3</sup> · Stefan A. Koerber<sup>1,2,3</sup> · Gerald Major<sup>1,2,3</sup> · Markus Alber<sup>1,2,3</sup> · Sati Akbaba<sup>1,2,3</sup> · Jürgen Debus<sup>1,2,3,4,5</sup> · Juliane Hörner-Rieber<sup>1,2,3,5</sup>



### Challenges for patients:

- **65% complaint rate of at least 1 item**
  - Cold temperature
  - Noise
  - Duration of treatment
  - Paresthesia
  - Uncomfortable positioning





# AI in MRgRT

## Patient acceptance

First prospective clinical evaluation of feasibility and patient acceptance of magnetic resonance-guided radiotherapy in Germany

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# AI in MRgRT

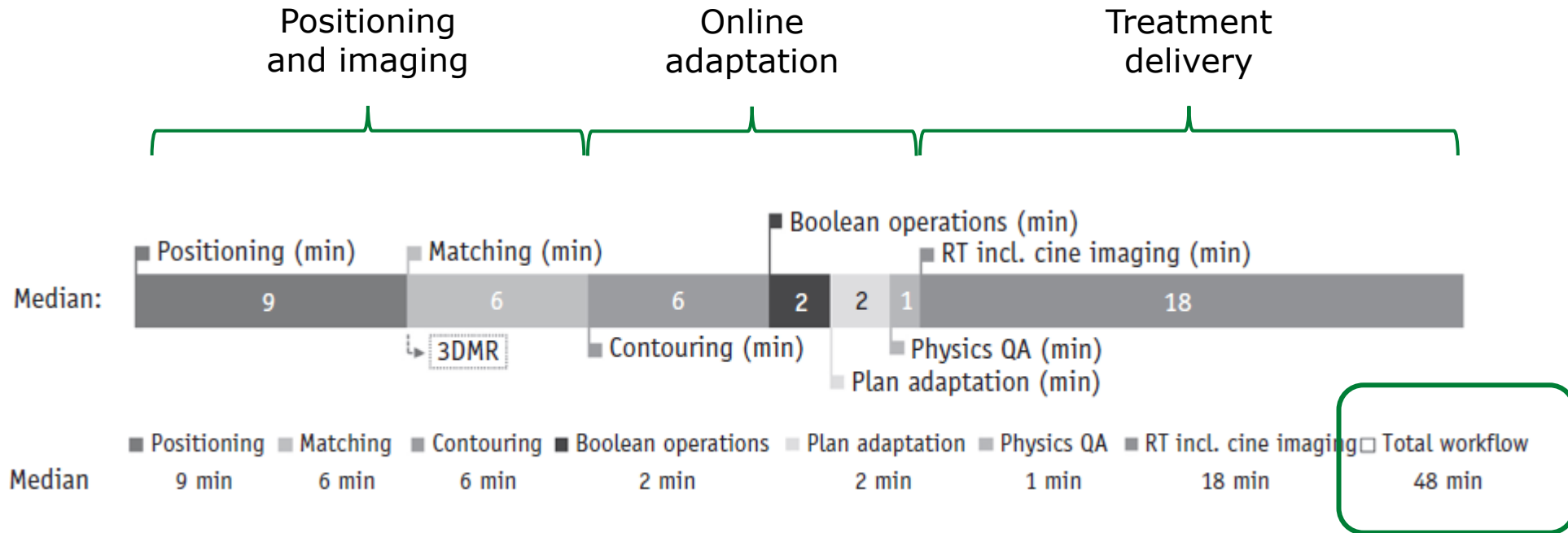
## Treatment duration

### Role of On-Table Plan Adaptation in MR-Guided Ablative Radiation Therapy for Central Lung Tumors

Tobias Finazzi, MD, Miguel A. Palacios, PhD,  
Femke O.B. Spoelstra, MD, PhD, Cornelis J.A. Haasbeek, MD, PhD,  
Anna M.E. Bruynzeel, MD, PhD, Ben J. Slotman, MD, PhD,  
Frank J. Lagerwaard, MD, PhD, and Suresh Senan, MRCP, FRCR, PhD

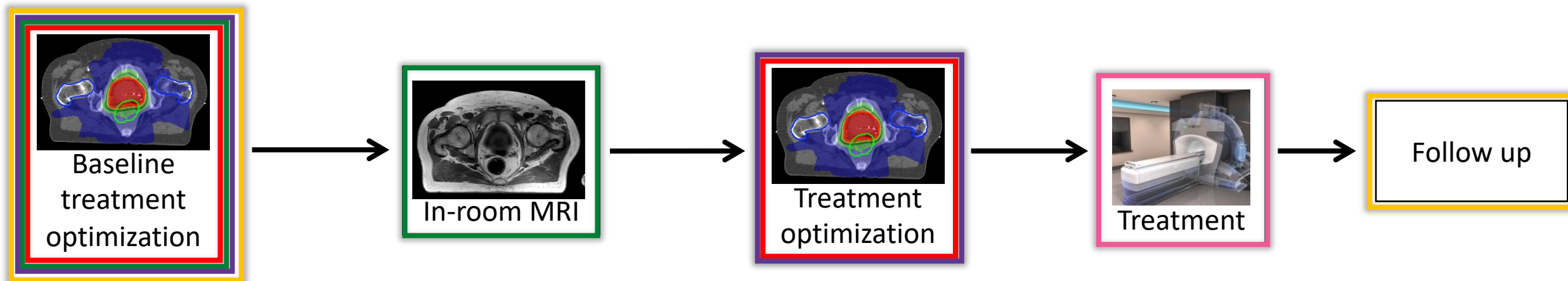
Department of Radiation Oncology, Amsterdam University Medical Centers, Vrije Universiteit Amsterdam, The Netherlands

Received Dec 10, 2018. Accepted for publication Mar 20, 2019.



# MRgRT workflow

## Where can AI help?



Automatic segmentation

Synthetic CT generation

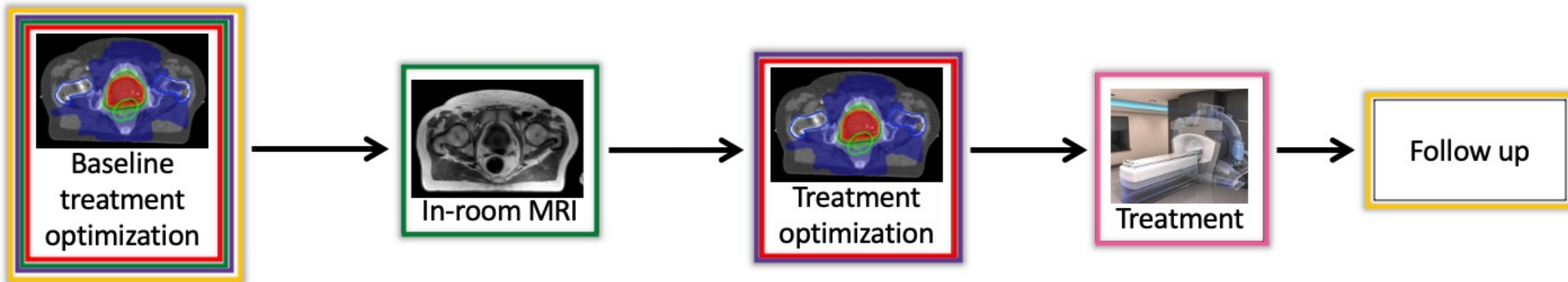
Dose prediction and automatic planning

Motion tracking

Outcome prediction

# MRgRT workflow

## Where can AI help?



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# Automatic segmentation

Why?



# Automatic segmentation

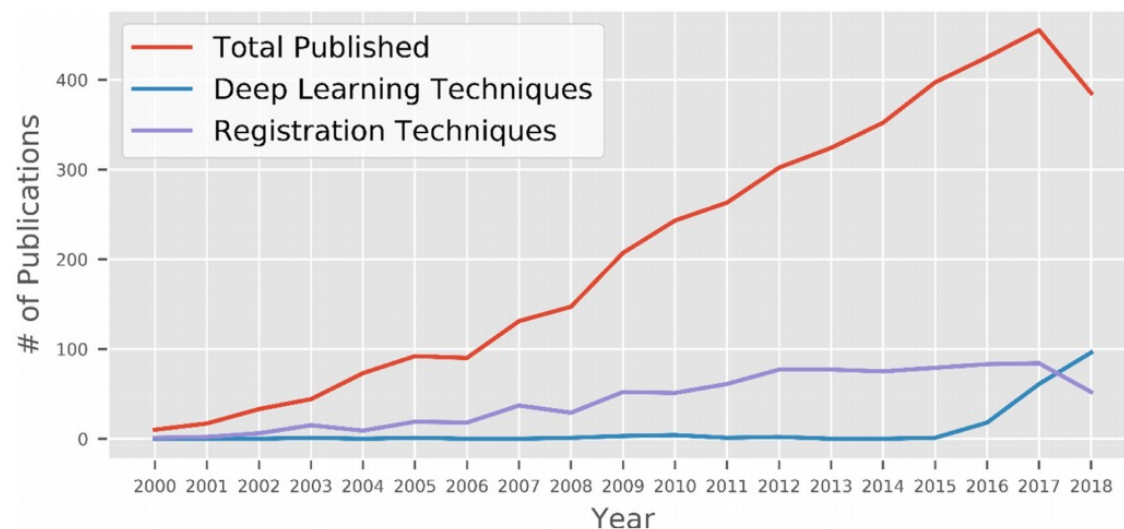
## DL is now well established



ELSEVIER

Seminars in  
RADIATION  
ONCOLOGY

### Advances in Auto-Segmentation

Carlos E. Cardenas, PhD, Jinzhong Yang, PhD, Brian M. Anderson, MS,  
Laurence E. Court, PhD, and Kristy B. Brock, PhD

- **Deep learning auto-segmentation algorithms have quickly become the state-of-the-art in medical image segmentation**
- some applications produce better results than the measured inter- and intraobserver contouring variability

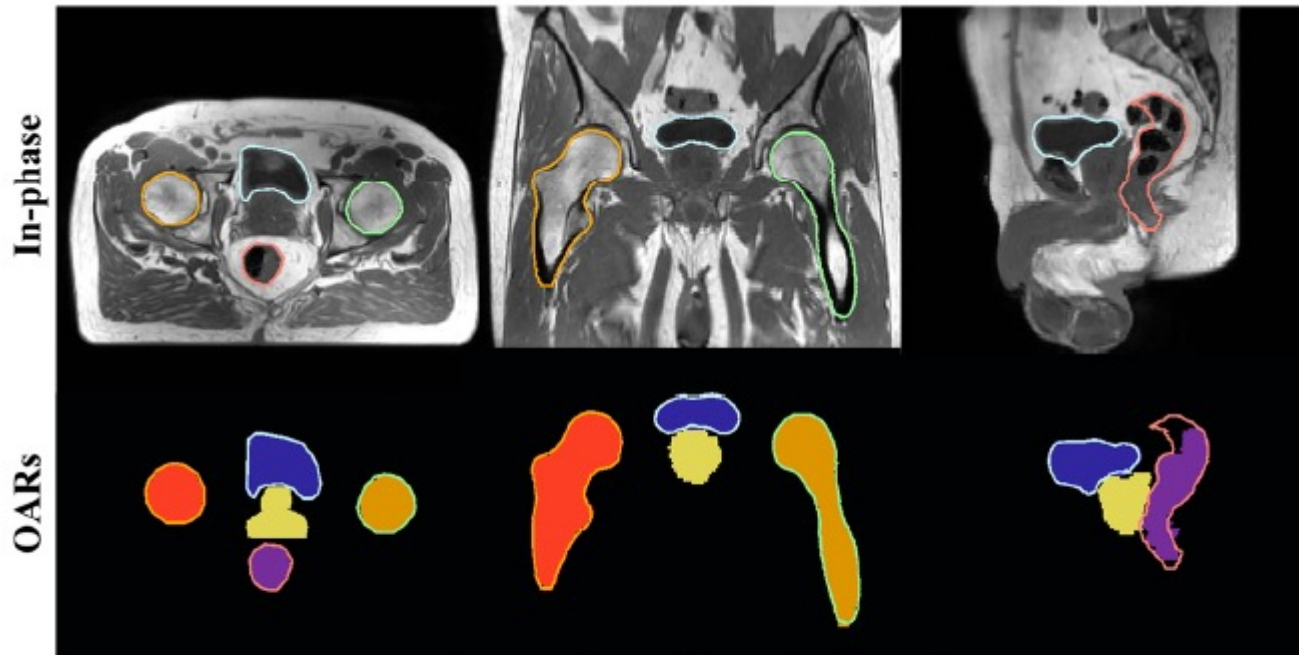
# Automatic segmentation

DL is now well established

## Clinical implementation of MRI-based organs-at-risk auto-segmentation with convolutional networks for prostate radiotherapy

Mark H. F. Savenije<sup>1,2†</sup>, Matteo Maspero<sup>1,2\*†</sup>, Gonda G. Sikkens<sup>1</sup>, Jochem R. N. van der Voort van Zyp<sup>1</sup>, Alexis N. T. J. Kotte<sup>1</sup>, Gijsbert H. Bol<sup>1</sup> and Cornelis A. T. van den Berg<sup>1,2</sup>

### OARs and target volume



	Bladder	Rectum	Fem <sub>L</sub>	Fem <sub>R</sub>	CTV
DeepMedic					/
Clinical					

#### Automatic segmentation is:

- Less intra- and interobserver variability
- Reduce manual segmentation time during Online Adaptation
- **Time efficient**
- **Improve consistency and reproducibility**



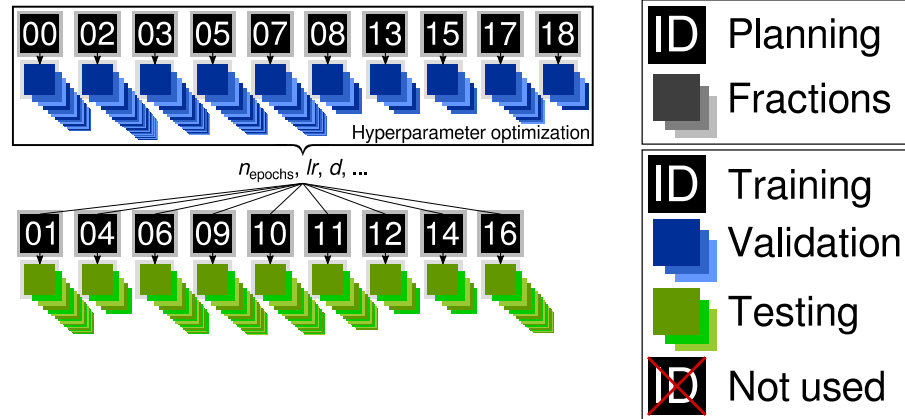


Wilhelm Sander-Stiftung  
fördert medizinische Forschung

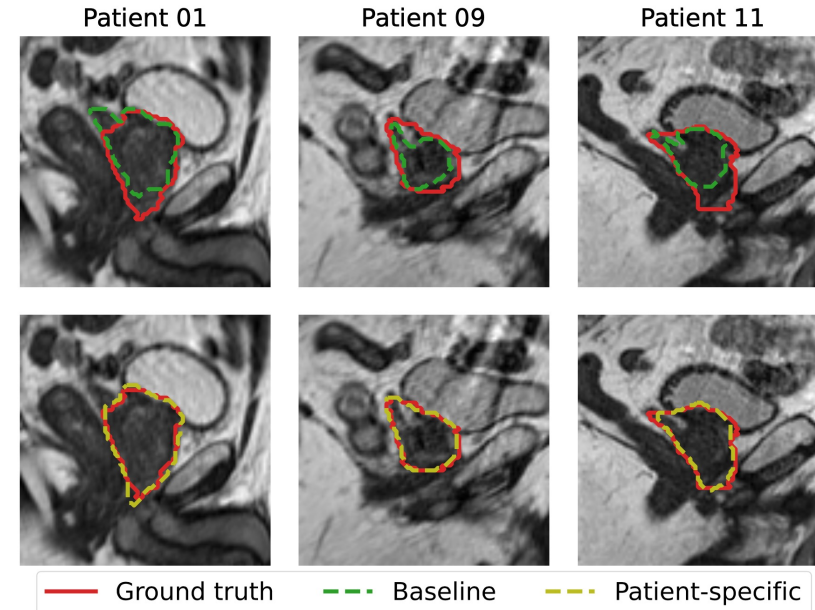
# Automatic segmentation

## Exploit planning knowledge

### Patient-specific fine tuning



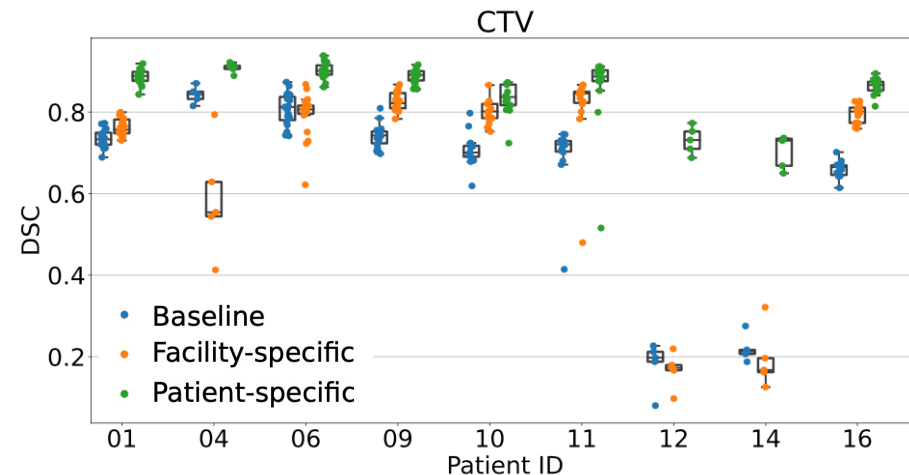
- Make use of prior information from **patient-specific** planning images for fraction image segmentation



M. Kawula



PD Dr. C. Kurz

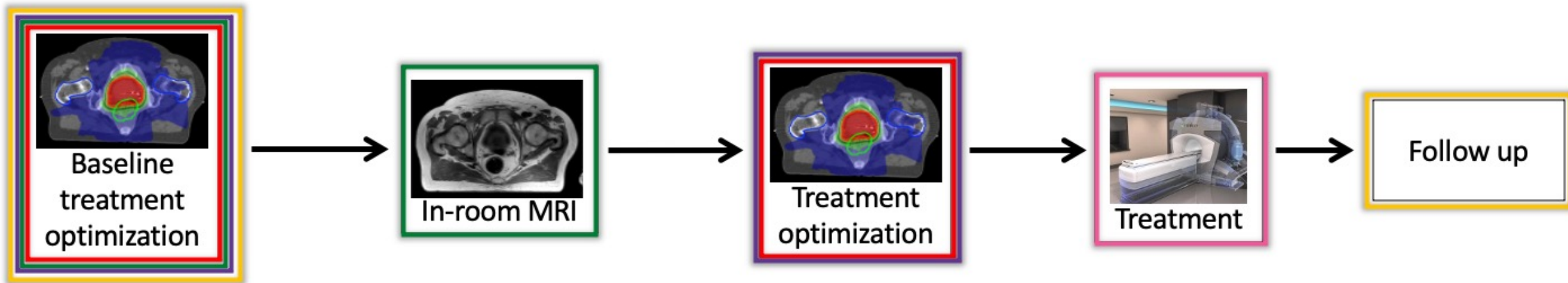


Kawula, Landry, Kurz. Under review



# MRgRT workflow

## Where can AI help?



Automatic segmentation

Synthetic CT generation

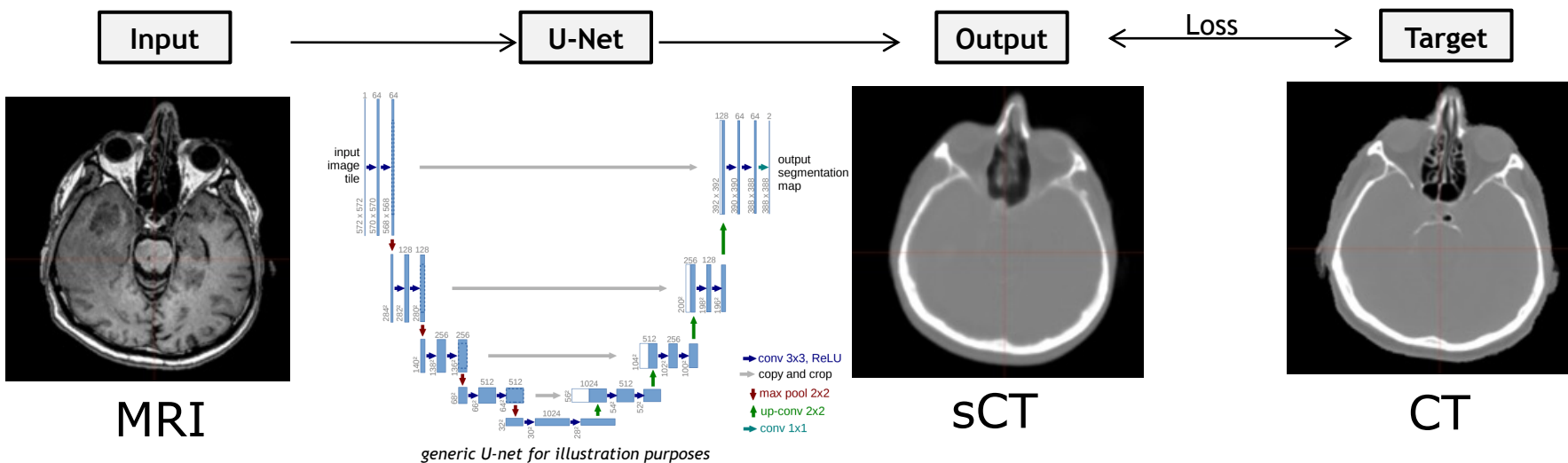
Dose prediction and automatic planning

Motion tracking

Outcome prediction

# Synthetic CT generation


## Electron Density map



Neppl, Landry, et al. Acta Oncol 2019  
Spadea et al. IJROBP 2019

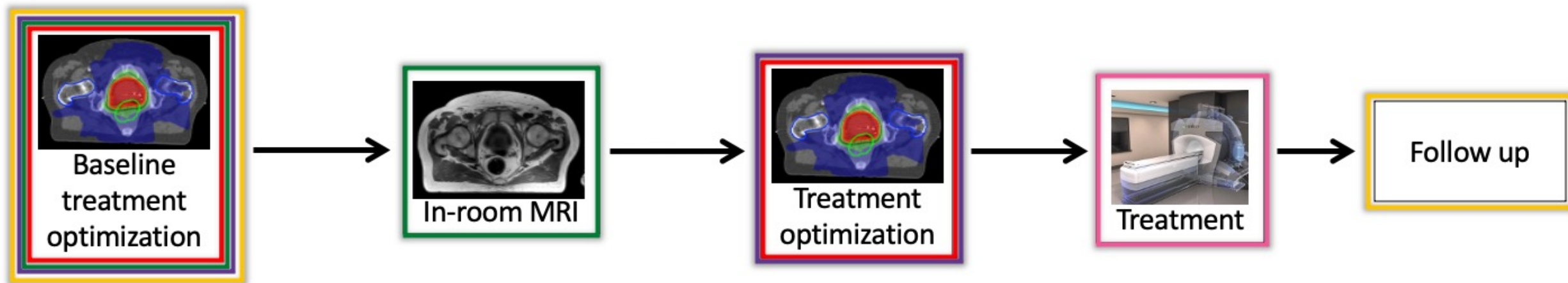
**Synthetic CT Generation is:**

- Time saving
- Less radiation exposure
- **Allows for a MR-only workflow**
- Reduces uncertainties of image registration



# MRgRT workflow

## Where can AI help?



Automatic segmentation

Synthetic CT generation

Dose prediction and automatic planning

Motion tracking

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# Automatic planning

## MRgRT

Original Article

First experience of autonomous, un-supervised treatment planning integrated in adaptive MR-guided radiotherapy and delivered to a patient with prostate cancer

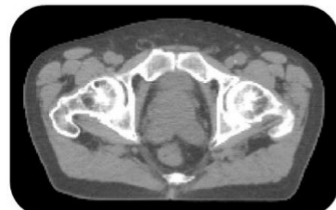


Luise A. Künzel<sup>a,\*</sup>, Marcel Nachbar<sup>a</sup>, Markus Hagmüller<sup>a</sup>, Cihan Gani<sup>b</sup>, Simon Boeke<sup>b</sup>, Daniel Zips<sup>b,c</sup>, Daniela Thorwarth<sup>a,c</sup>

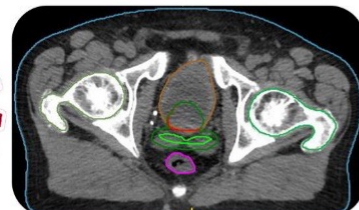
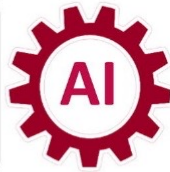
### Autonomous, un-supervised planning pipeline

3 min

DL-Annotation

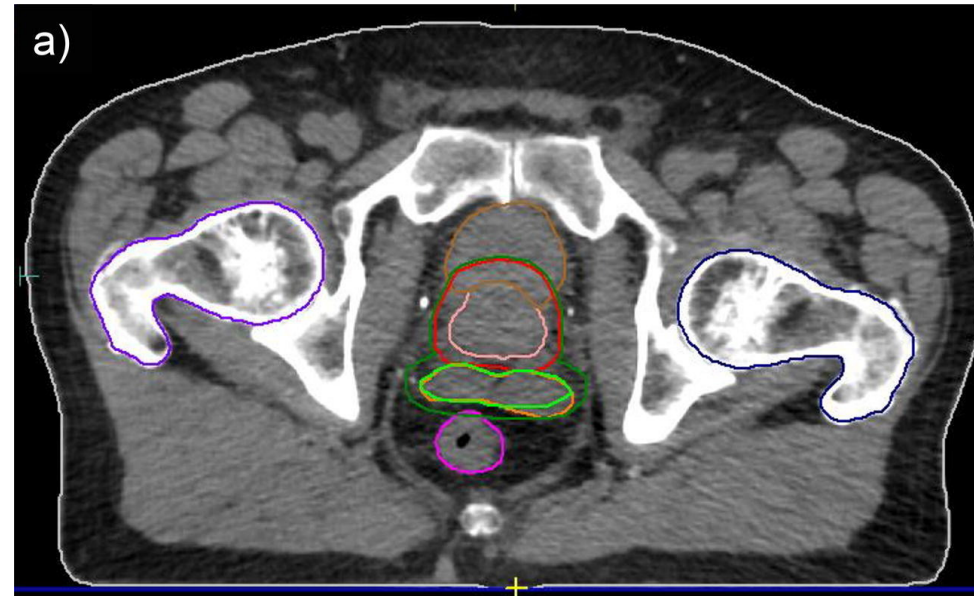


CT-Simulation



CT + structure set

Autonomous



- PTV60
- CTV60
- PTV57.6
- CTV57.6
- Rectum
- Bladder
- Penile Bulb
- Seminal vesicles
- Femoral head right
- Femoral head left
- External

# Automatic planning

## MRgRT

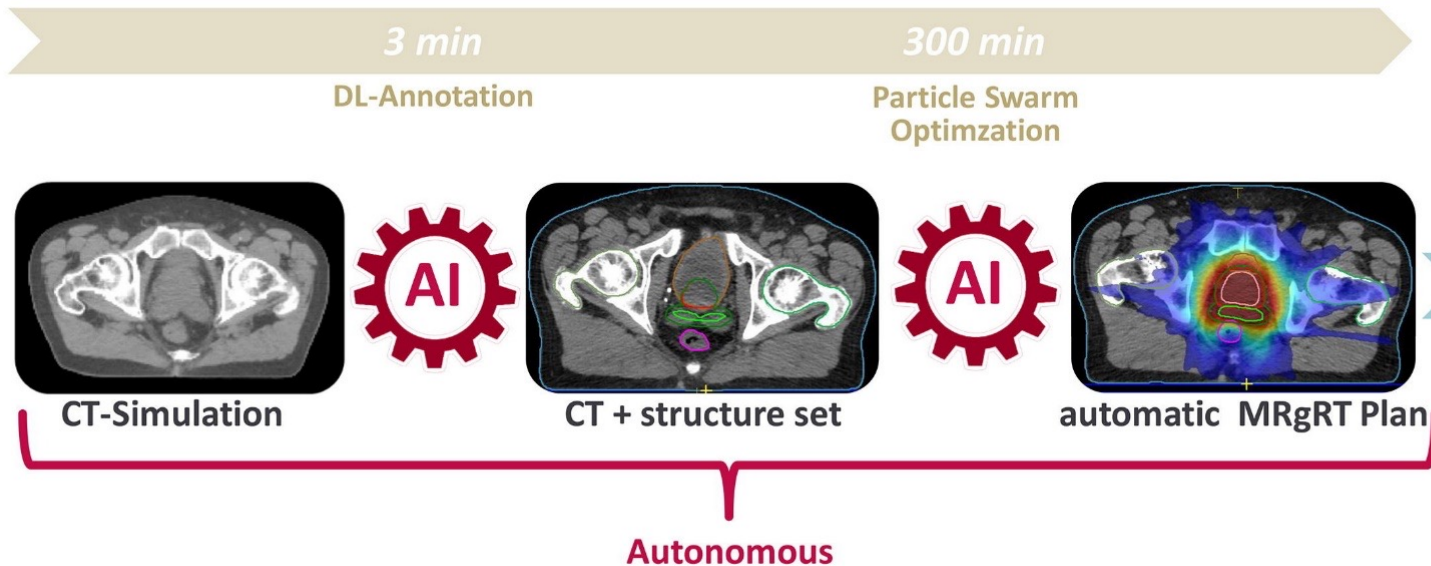
Original Article

First experience of autonomous, un-supervised treatment planning integrated in adaptive MR-guided radiotherapy and delivered to a patient with prostate cancer



Luise A. Künzel<sup>a,\*</sup>, Marcel Nachbar<sup>a</sup>, Markus Hagmüller<sup>a</sup>, Cihan Gani<sup>b</sup>, Simon Boeke<sup>b</sup>, Daniel Zips<sup>b,c</sup>, Daniela Thorwarth<sup>a,c</sup>

### Autonomous, un-supervised planning pipeline



# Automatic planning

## MRgRT

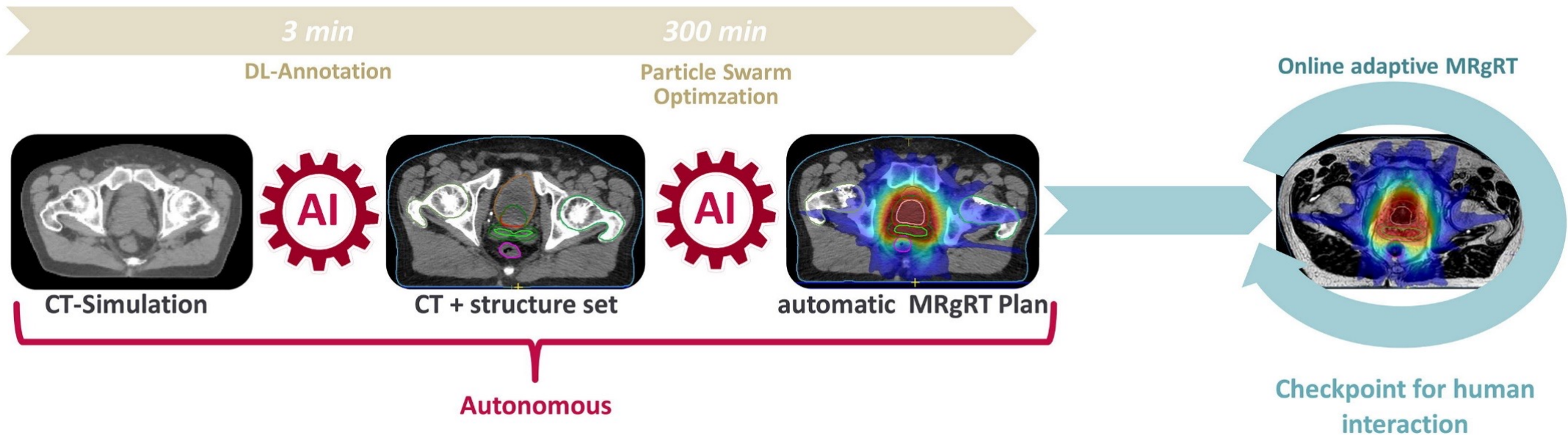
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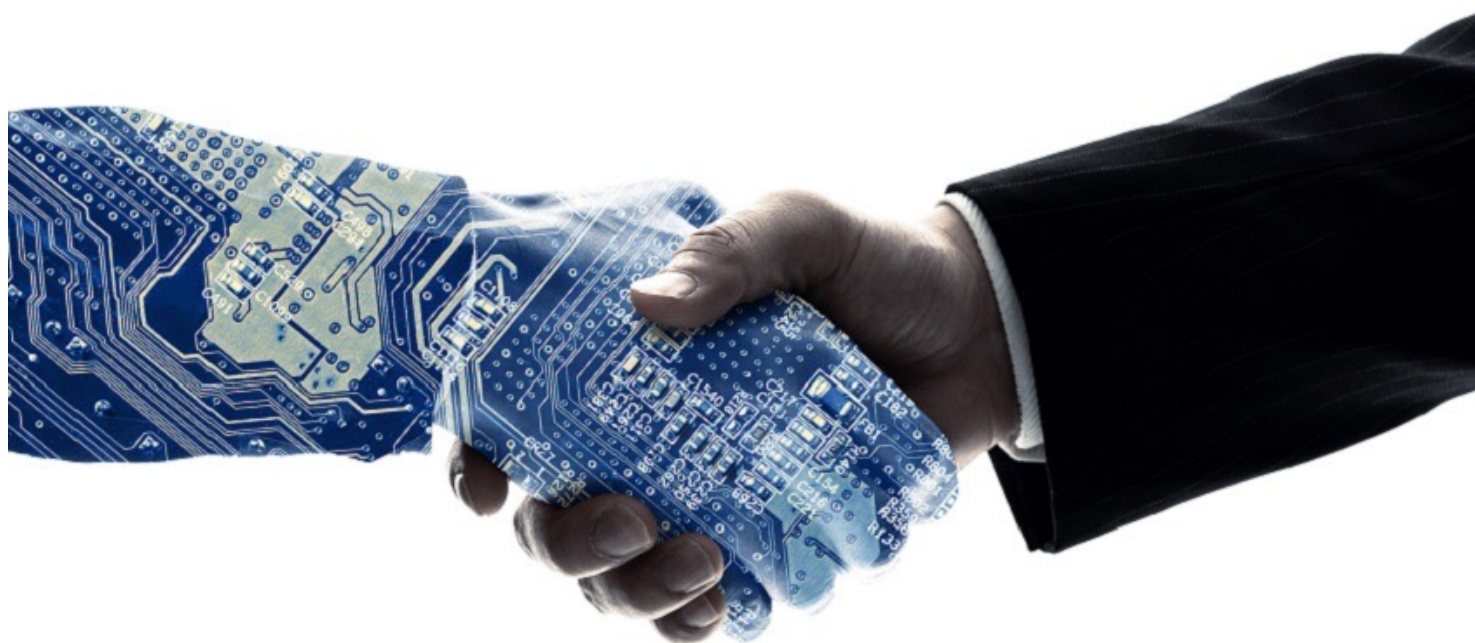
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### Autonomous, un-supervised planning pipeline



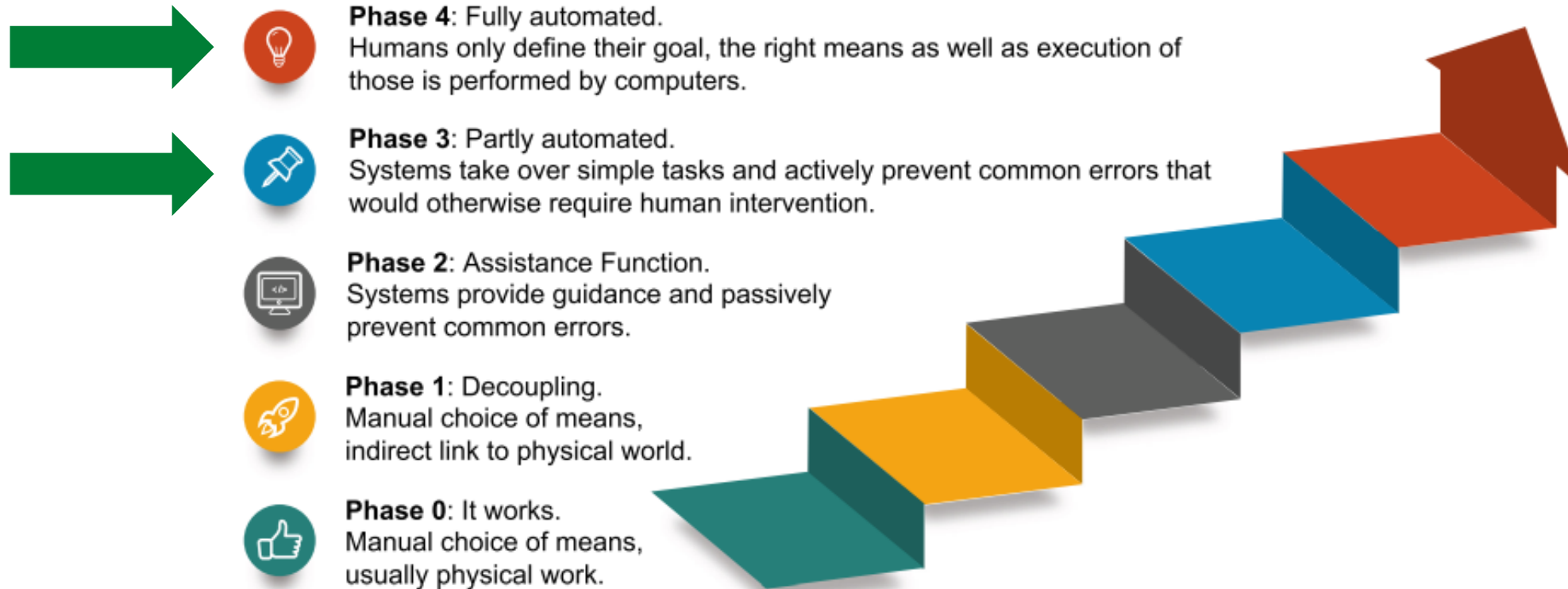
Can we trust AI?

MRgRT



## Stepwise implementation

### AI



**Fig. 1.** Automation phases



# Stepwise implementation


## MRgRT

### ▪ Open Questions:

- Can AI **replace humans**? Is AI a **threat to human jobs**?
  - Changing in roles: from operator to monitor/supervisor
  - Managing of automation
- Will AI **impact our education/training**?
  - Reduction of human skills/competencies → human interventions still possible?
- Can we **trust and rely on AI**?
  - Transparency in AI operations affects human trust
  - Over-reliance vs under-reliance
  - **QA**
- Is AI a **tool** or a **teammate**?
  - Complex human-machine interaction

Article

## Architectural Framework for Exploring Adaptive Human-Machine Teaming Options in Simulated Dynamic Environments

Azad M. Madni \* and Carla C. Madni 




# Human-Machine Teams

## MRgRT

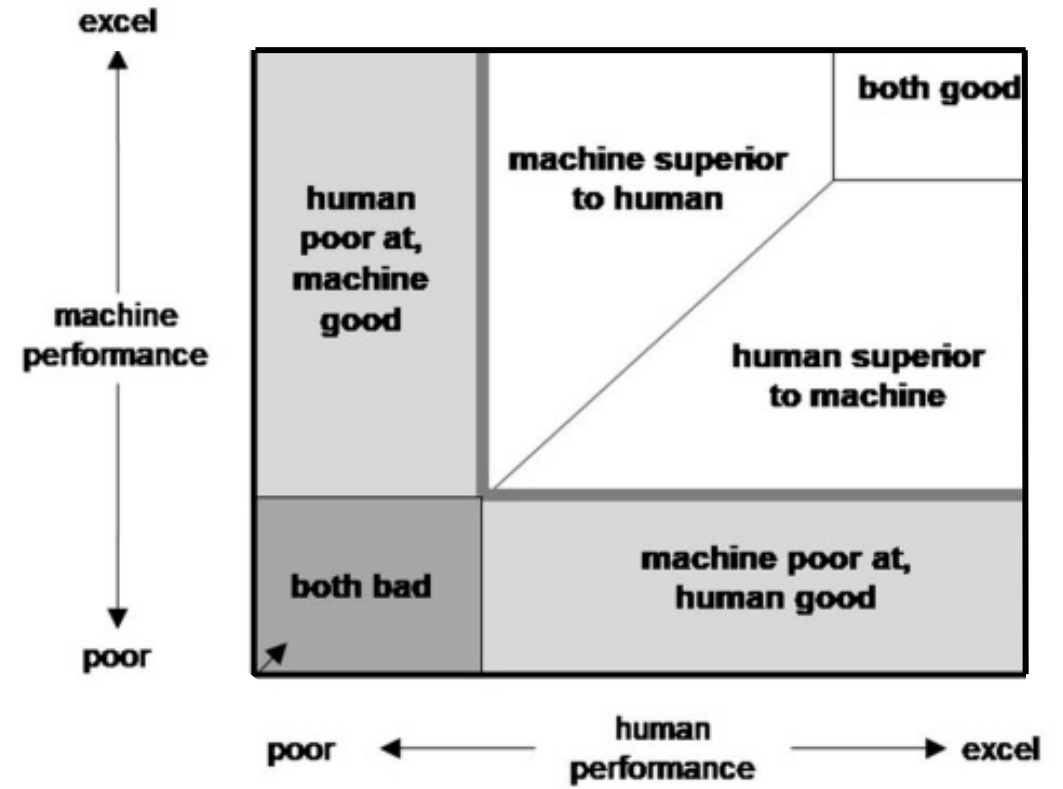
- Shared task execution

Article

# Architectural Framework for Exploring Adaptive Human-Machine Teaming Options in Simulated Dynamic Environments

Azad M. Madni \* and Carla C. Madni 

## HUMAN-MACHINE TEAMING

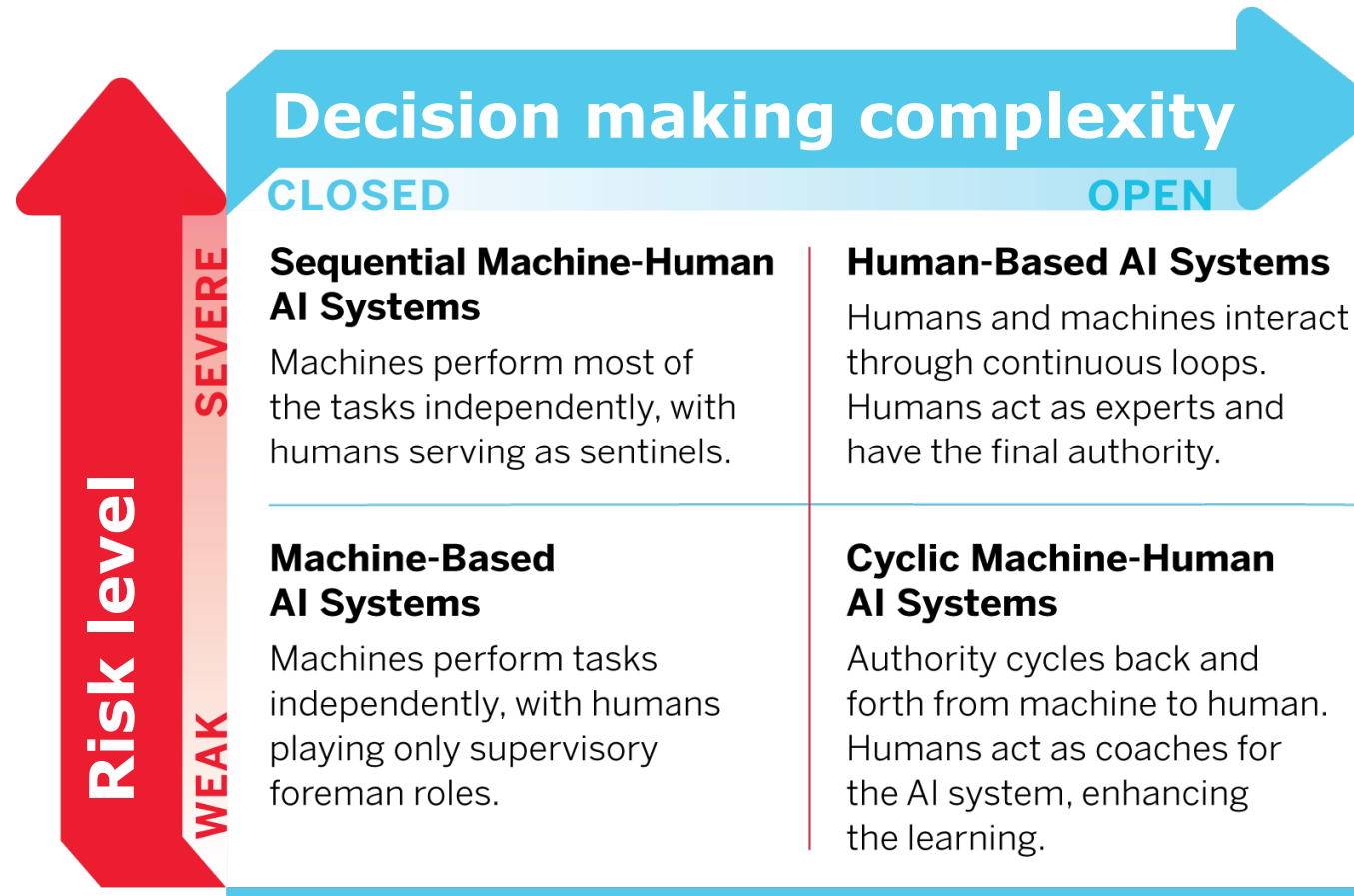


# What does the human face of AI look like?

By Maria Jesus Saenz, Elena Revilla and Cristina Simon

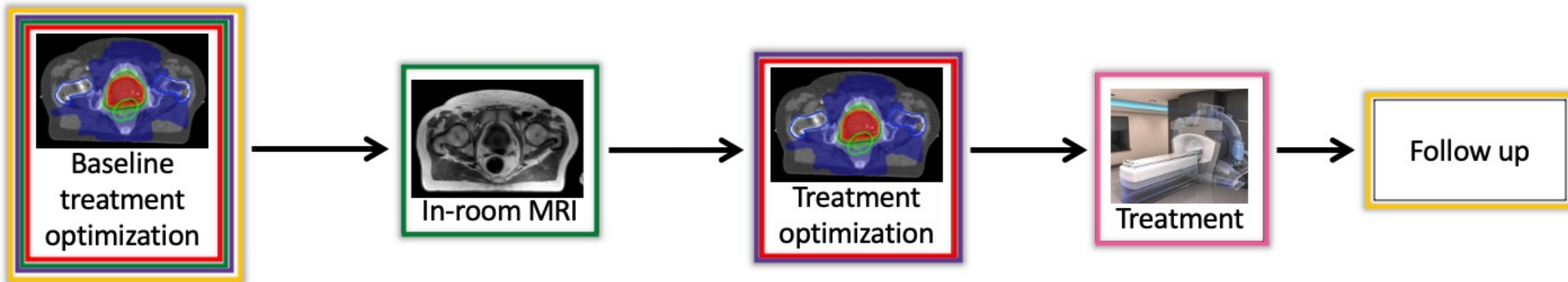
## Human-Machine Teaming

### Decision making



# MRgRT workflow

## Where can AI help?



Automatic segmentation

Synthetic CT generation

Dose prediction and automatic planning

Motion tracking

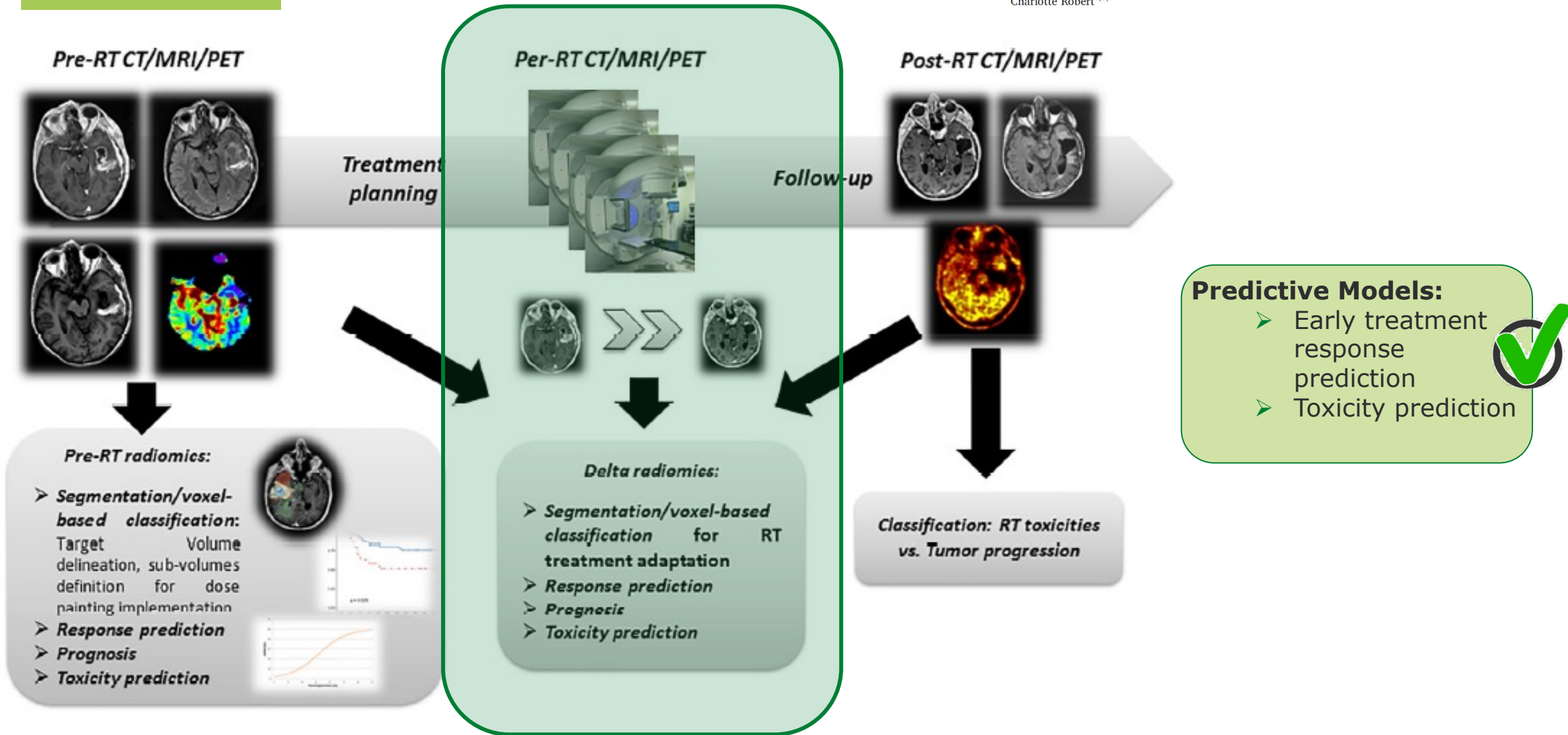
Outcome prediction

# Outcome prediction

## Radiomics

Reinventing radiation therapy with machine learning and imaging biomarkers (radiomics): State-of-the-art, challenges and perspectives

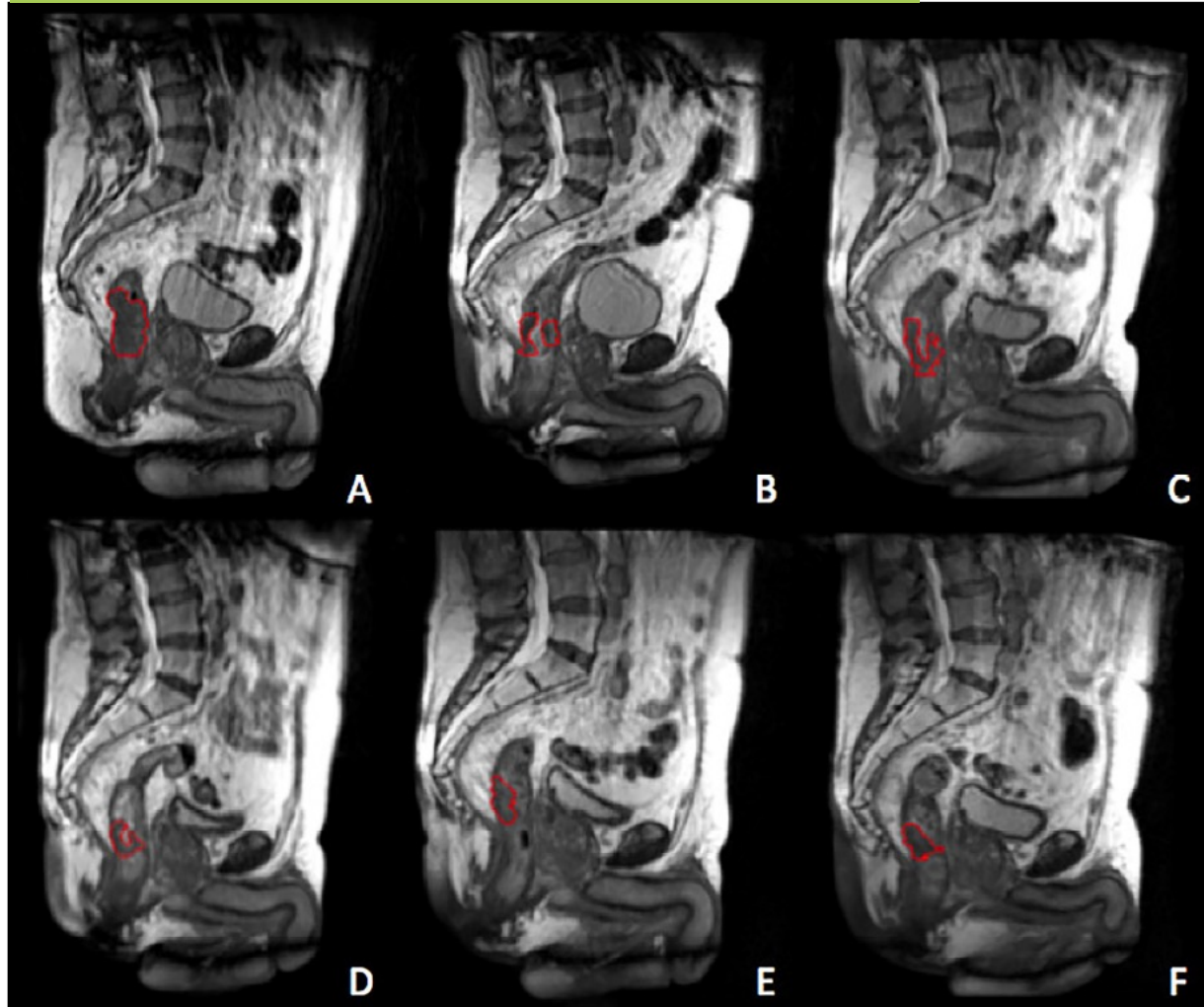
Laurent Derclé<sup>a,1</sup>, Theopraste Henry<sup>b,c,1</sup>, Alexandre Carré<sup>b,d</sup>, Nikos Paragios<sup>e</sup>, Eric Deutsch<sup>b,d</sup>, Charlotte Robert<sup>b,d,\*</sup>






# Outcome prediction

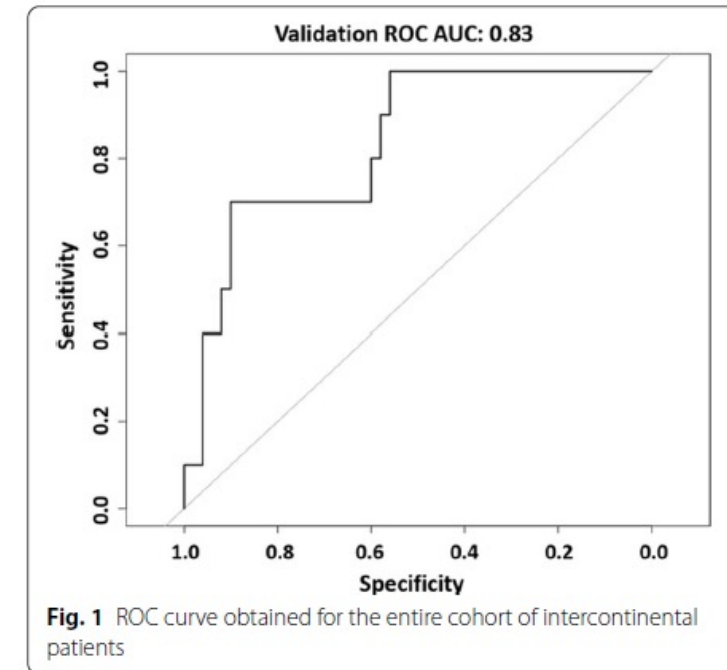
## Early treatment response



**FIGURE 1** | Gross tumour volum (GTV) delineated at the treatment simulation (A) and at the different treatment fractions selected for the delta-radiomics analysis, corresponding to BED levels of 13 Gy (B), 26 Gy (C), 40 Gy (D), 54 Gy (E) and 67 Gy (F). The GTV is represented by the red contour.

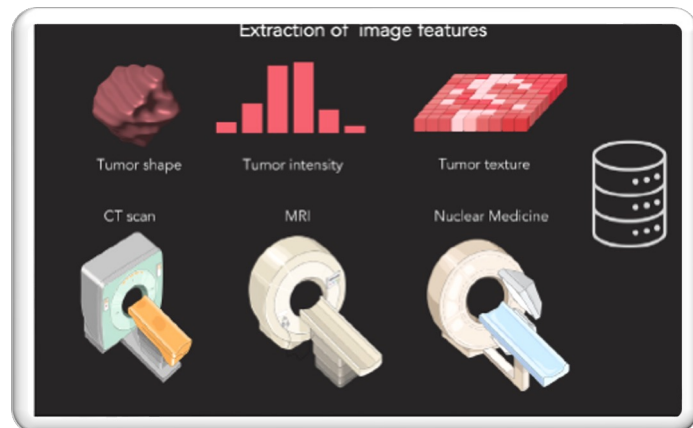
Applicability of a pathological complete response magnetic resonance-based radiomics model for locally advanced rectal cancer in intercontinental cohort

Luca Boldrini<sup>1</sup>, Jacopo Lenkowitz<sup>1</sup>, Lucia Clara Orlandini<sup>2</sup>, Gang Yin<sup>2</sup>, Davide Cusumano<sup>1</sup>, Giuditta Chiloiro<sup>1</sup>, Nicola Dinapoli<sup>1</sup>, Qian Peng<sup>2\*</sup> , Calogero Casà<sup>1</sup>, Maria Antonietta Gambacorta<sup>1</sup>, Vincenzo Valentini<sup>1</sup> and Jinyi Lang<sup>2</sup>

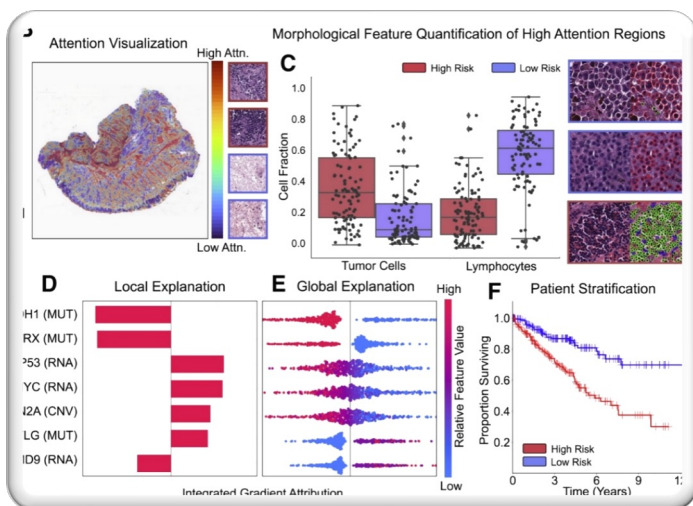


# Outcome prediction

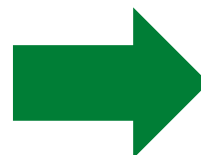
## Individualized radiotherapy



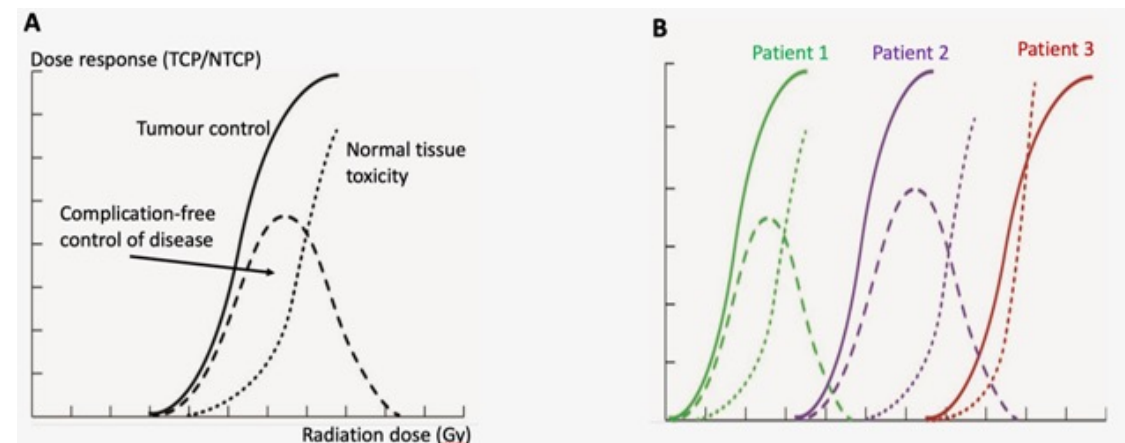
+



Imaging Biomarkers



Clinical/  
Biological/  
Genomic  
Biomarkers



Legend Figure 1

A) The classical tumour control probability (TCP) and normal tissue complication probability (NTCP) curves. -The aim is to shift the tumour control curve left and the normal tissue curve right.

B) Future individual dose response curve, combining GARD and susceptibility to radiotoxicity to predict the benefit of radiation for an individual patient. Patient 1- tumour and normal tissue are sensitive to radiation but therapeutic window is narrow. Patient 2- Tumour is relatively sensitive and high normal tissue tolerance resulting in a very wide therapeutic window. Patient 3- Tumour is radioresistant with virtually no therapeutic window.

Poortmans

### Predictive Models:

- Individualized treatments
- Fully exploit **individual therapeutic window**



# AI in cancer therapy

## Perspective on MRgRT

- **AI can support MRgRT:**
  - **AI is a tool** & can increase **quality, standardization and acceleration** of the different treatment steps
  - AI algorithms are applicable to **almost all aspects** of the MRgRT workflow
  - Autosegmentation is one of the most visible applications
  - AI can provide predictive and prognostic information on outcome and FU



# AI in cancer therapy

## The way forward



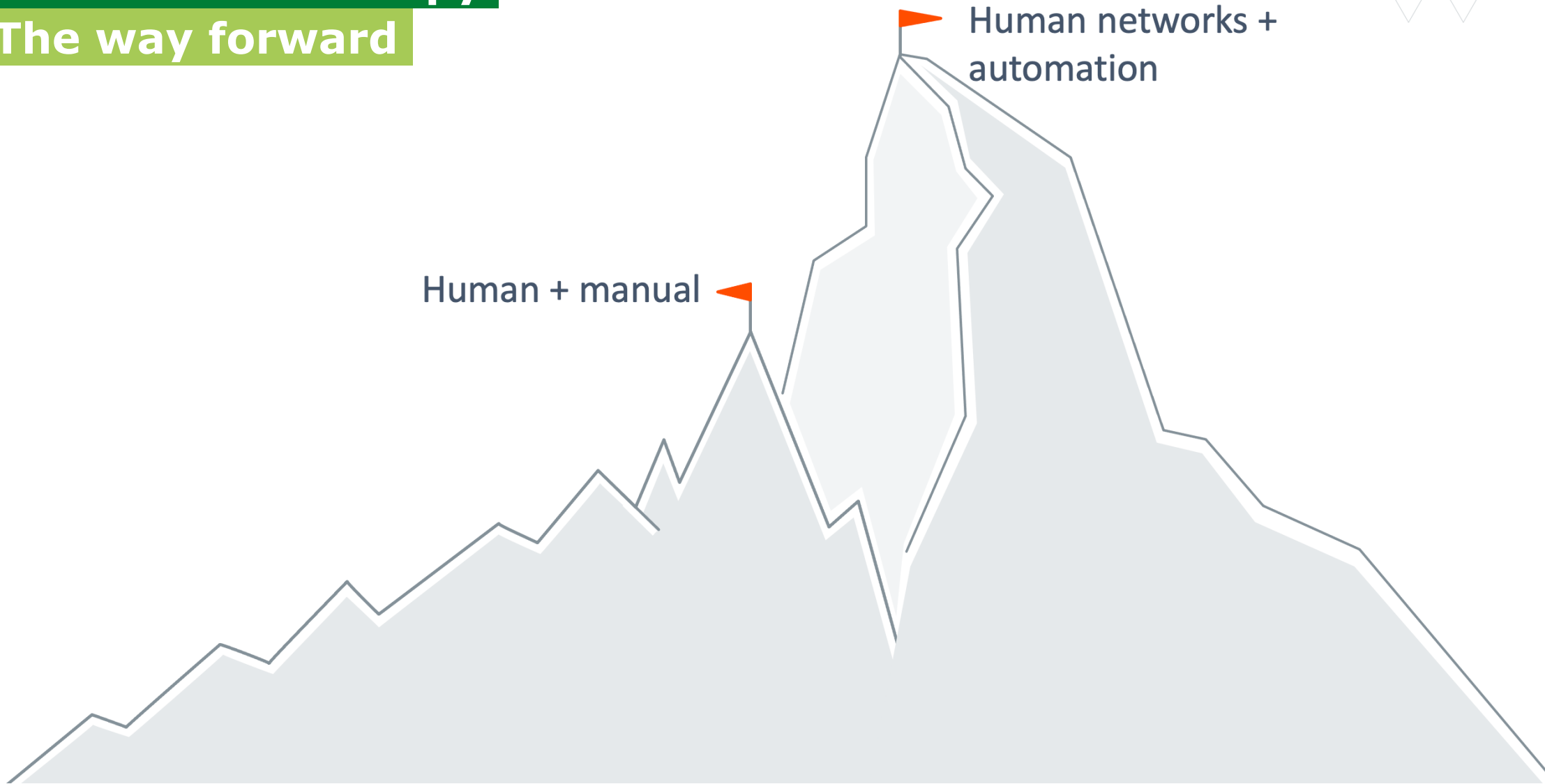
# AI in cancer therapy

## The way forward



# AI in cancer therapy

## The way forward



**Thank you**

**For your attention!**



@stef\_corradini



Stefanie Corradini



Stefanie.corradini@med.lmu.de