Innovation:

AI and error prevention

Prof. Dr. Dirk Verellen

Universiteit Antwerpen

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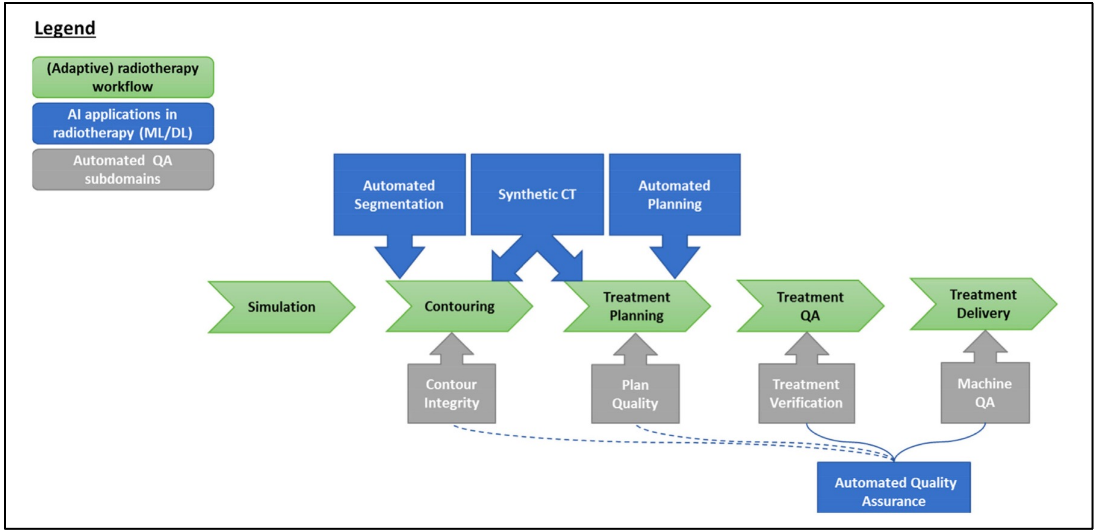
Topzorg in radiotherapie

AI in RT

- Autosegmentation
- Autoplanning
- Radiation physics quality assurance
- Respiration motion management
  - personalized PTV
  - Markerless tumour tracking
  - ...
- Predicitve analytics:
  - Image guidance
  - Response modeling
  - ...



Vandewinckele L, Claessens M *et al.* Radiother Oncol, 2020

Outline

- AI in RT
  - Standardization, safety and quality
- AI for QA: some examples
  - Reducing variation and improving plan quality
  - Predictive intelligence
- QA of AI: some examples
  - Independent autosegmentation
  - Recommendations on implementation and QA of AI

Efficiency, Standardization, Quality & Safety

- Do we need state-of-the-art **mainstream** equipment **for many** patients or **dedicated** equipment **for a few**?

- Do we need **standardized** treatment or **individualized** treatment tailored to the patient?

Not necessarily the same question

Not necessarily a contradiction

Efficiency, Standardization, Quality & Safety

Global Journal of Information Technology

SPROC ScienceParK Research, Organization & Counseling

Global Journal of Information Technology

Volume 05, Issue 2, (2015) 56-61

http://sproc.org/ojs/index.php/gjit

Assessing productivity to address safety concerns for information technology and promoting global standardization within aviation practices

AORN JOURNAL

THE OFFICIAL VOICE OF PERIOPERATIVE NURSING

Patient Safety First

Using Aviation Safety Measures to Enhance Patient Outcomes

Russell M. Rivers, Diane Swain RN, William R. Nixon

First published: 01 January 2003 | https://doi.org/10.1016/S0001-2092(06)61385-9 | Citations: 18

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ABSTRACT

Recent media reports have put a spotlight on the increasing number of medical errors occurring in US health care institutions. In contrast to health care's increasing error rate, the aviation industry is experiencing a decreasing error rate. Could the safety techniques used in the aviation industry be applied to health care? This article explores that question. The dynamics of the surgical suite are not unlike those of the cockpit of an airplane; therefore, perioperative services was selected to pilot test the aviation model of safety training. *AORN J 77* (Jan 2003) 158-162.

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Automated planning: an example (1)

Wang *et al. Radiation Oncology* (2017) 12:85
DOI 10.1186/s13014-017-0822-z

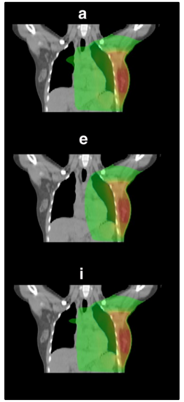
Radiation Oncology

RESEARCH Open Access

Is it possible for knowledge-based planning to improve intensity modulated radiation therapy plan quality for planners with different planning experiences in left-sided breast cancer patients?

Juanqi Wang[1,2], Weigang Hu[1,2*], Zhaozhi Yang[1,2*], Xiaohui Chen[1,2], Zhiqiang Wu[1,2], Xiaoli Yu[1,2], Xiaoma
Saiquan Lu[1,2], Kaixuan Li[1,2] and Gongyi Yu[1,2]

IMPROVE CONSISTENCY and QUALITY



$$\delta = \frac{P_{manual} - P_{KBP}}{P_{manual}} \times 100,$$

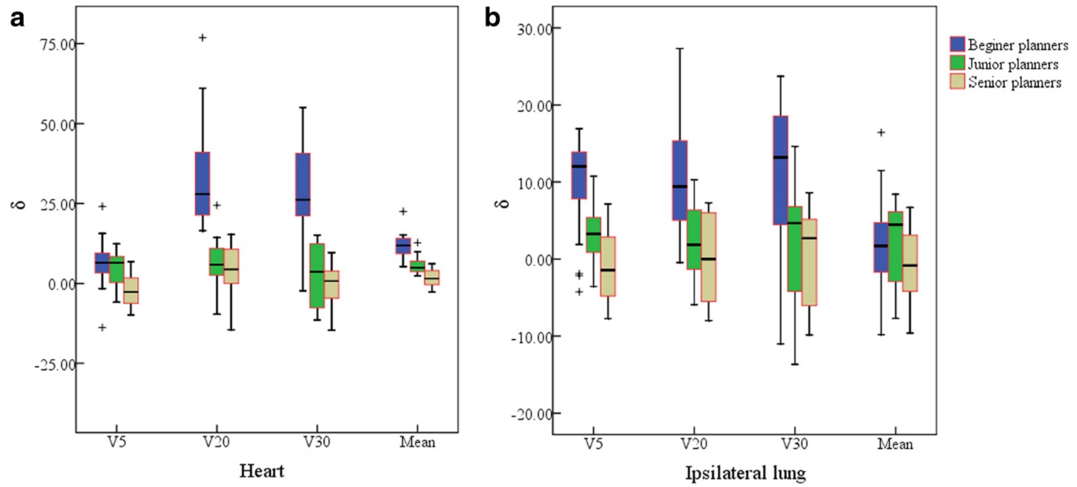
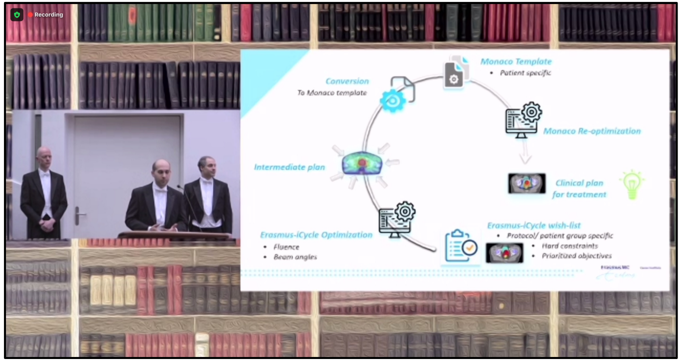
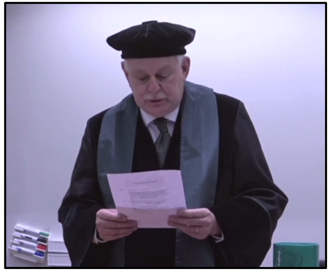


Fig. 2 The box plots depicting the effect of KBP implementation on (**a**) the heart and (**b**) the ipsilateral lung dose for planners with each level of planning experiences. δ means the relative OAR dose deduction

Automated planning: an example (2)

- Autoplanning can **reduce variation** between non-experienced and experience planners, and **improve overall quality and consistency**.
- Typically, “comparative” studies are performed by different (human) planners under different conditions (eg available planning time, experience).
- *Erasmus MC’s iCycle* is nice example of how automated planning can be used to generate non-biased, objective plans to compare different treatment delivery techniques: “**bias free technique comparison**”





Automated planning: an example (2)

- Gastric cancer: improving quality and consistency

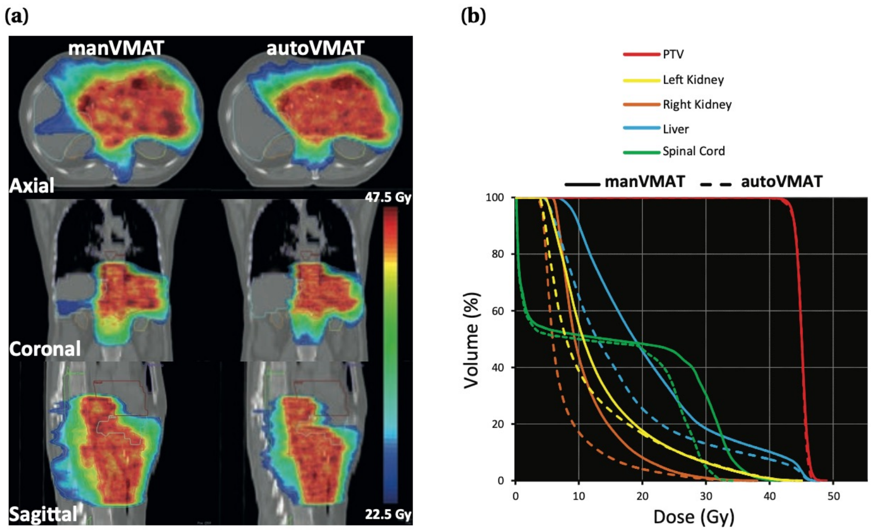
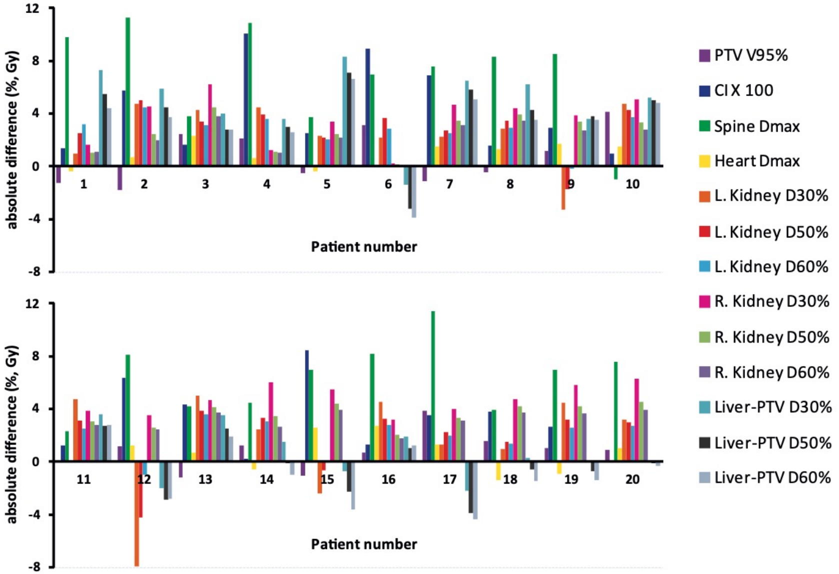


Figure 4.1: a) Comparison of dose distributions for the manVMAT (left) and autoVMAT plans (right) for patient 8 on the axial, coronal and sagittal planes, **b)** Dose-volume histograms for the manVMAT (solid lines) and the autoVMAT (dashed lines) plans of this patient.

Courtesy A. Sharfo

Automated planning: an example (2)

- Gastric cancer: improving quality and consistency



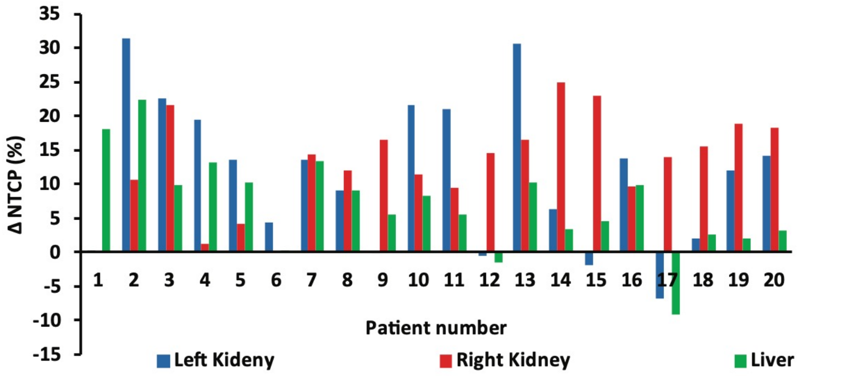


Figure 4.3: Differences in the predicted normal tissue complication probabilities (NTCP) between autoVMAT and manVMAT plans for the 20 study patients. Positive values are in favor of the autoVMAT plans.

Figure 4.2: Differences in dosimetric plan parameters between autoVMAT and manVMAT plans for each of the 20 study patients. Positive values are in favor of the autoVMAT plans.

Courtesy A. Sharfo

Automated planning: an example (2)

- Cervical Cancer:
  - exploring treatment options

Comparison of VMAT and IMRT for Cervical Cancer

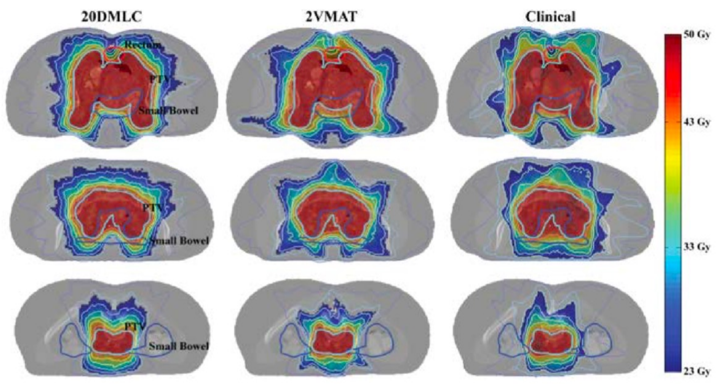


Figure 6.1: Axial slices for patient 8 showing the differences in dose distribution between 20DMLC, 2VMAT, and clinical plans. The shown isodose lines are 30%, 40%, 50%, 60%, 70%, 80%, 95% and 107% of the prescribed dose, respectively.

Table 6.2: Pair-wise comparisons of planning strategies.

		20DMLC	12DMLC		9DMLC		2VMAT		VMAT		Clinical	
			p-value	*Pts*	*p-value*	*Pts*	*p-value*	*Pts*	*p-value*	*Pts*	*p-value*	*Pts*
	a		NS	(6 | 4)	.031	(7 | 3)	NS	(7 | 3)	.006	(9 | 1)	.002	(10 | 0)
	b		.037	(9 | 1)	.004	(9 | 1)	.002	(10 | 0)	.008	(9 | 1)	.002	(10 | 0)
20DMLC	c		.002	(10 | 0)	.002	(10 | 0)	.004	(10 | 0)	.002	(10 | 0)	.002	(10 | 0)
	d		.01	(8 | 2)	.006	(9 | 1)	.002	(10 | 0)	.002	(10 | 0)	.002	(10 | 0)
	e		NS	(8 | 2)	NS	(7 | 3)	.002	(10 | 0)	.002	(10 | 0)	.002	(10 | 0)
	a	1.1/15.2			NS	(6 | 4)	NS	(5 | 5)	NS	(8 | 2)	.002	(10 | 0)
	b	2.6/50.0			NS	(8 | 2)	.006	(9 | 1)	.02	(8 | 2)	.002	(10 | 0)
12DMLC	c	0.6/20.9			.002	(10 | 0)	.006	(9 | 1)	.004	(9 | 1)	.002	(10 | 0)
	d	0.5/43.0			NS	(7 | 3)	.004	(9 | 1)	.004	(10 | 0)	.004	(9 | 1)
	e	0.3/42.1			NS	(7 | 3)	.002	(10 | 0)	.004	(10 | 0)	.002	(10 | 0)
	a	1.2/15.3	0.1/15.8				.01	(3 | 7)	NS	(7 | 3)	.002	(10 | 0)
	b	4.8/51.1	2.2/52.3				.027	(8 | 2)	NS	(7 | 3)	.004	(9 | 1)
9DMLC	c	1.3/21.2	0.7/21.5				NS	(7 | 3)	NS	(7 | 3)	.004	(9 | 1)
	d	0.8/43.1	0.2/43.4				NS	(8 | 2)	.049	(8 | 2)	.006	(9 | 1)
	e	0.5/42.2	0.2/42.4				.004	(9 | 1)	.002	(10 | 0)	.002	(10 | 0)
	a	0.2/14.8	-0.9/15.3		-1.0/15.4				.012	(9 | 1)	.002	(10 | 0)
	b	9.0/53.2	6.4/54.4		4.2/55.5				NS	(5 | 5)	.01	(8 | 2)
2VMAT	c	1.7/21.4	1.1/21.7		0.5/22.1				.027	(9 | 1)	.002	(10 | 0)
	d	1.2/43.3	0.6/43.6		0.4/43.7				NS	(7 | 3)	.037	(8 | 2)
	e	1.3/42.6	1.0/42.8		0.8/42.9				NS	(8 | 2)	.014	(9 | 1)
	a	1.3/15.4	0.3/15.9		0.2/16.0		1.2/15.5				.004	(9 | 1)
	b	9.6/53.5	7.1/54.8		4.9/55.9		0.7/58.0				.002	(10 | 0)
VMAT	c	2.1/21.6	1.5/21.9		0.9/22.3		0.4/22.5				.002	(10 | 0)
	d	1.5/43.5	1.0/43.8		0.8/43.9		0.4/44.1				NS	(7 | 3)
	e	1.8/42.9	1.5/43.0		1.3/43.1		0.5/43.5				NS	(7 | 3)
	a	4.1/16.8	3.1/17.3		3.0/17.4		4.0/16.9		2.8/17.4			
	b	17.4/57.4	14.8/58.6		12.6/59.7		8.4/61.8		7.7/62.2			
Clinical	c	4.5/22.8	3.9/23.1		3.3/23.5		2.8/23.7		2.4/23.9			
	d	1.9/43.7	1.4/44.0		1.2/44.1		0.8/44.3		0.4/44.5			
	e	2.5/43.2	2.2/43.4		2.0/43.5		1.2/43.9		0.7/44.1			

Abbreviations: NS = no statistically significant difference i.e. $p > .05$.
In each comparison (table cell), going from top to bottom, data refer to (a) SB V_{45Gy}, (b) SB V_{15Gy}, (c) SB D_{mean}, (d) Bladder D_{mean}, and (e) Rectum D_{mean}. Below the table diagonal, the "A/B" in the cells refer to A: plan parameter value for the strategy along the vertical axis minus the parameter value for the strategy along the horizontal axis, averaged over the 10 patients in the study, B: average of the patient-mean OAR parameter values in the two compared strategies. Cells above the diagonal show p-values and "$(n|m)$": for n patients, the strategy indicated at the horizontal axis has lowest OAR dose, while for m patients the strategy mentioned at the vertical axis is superior.

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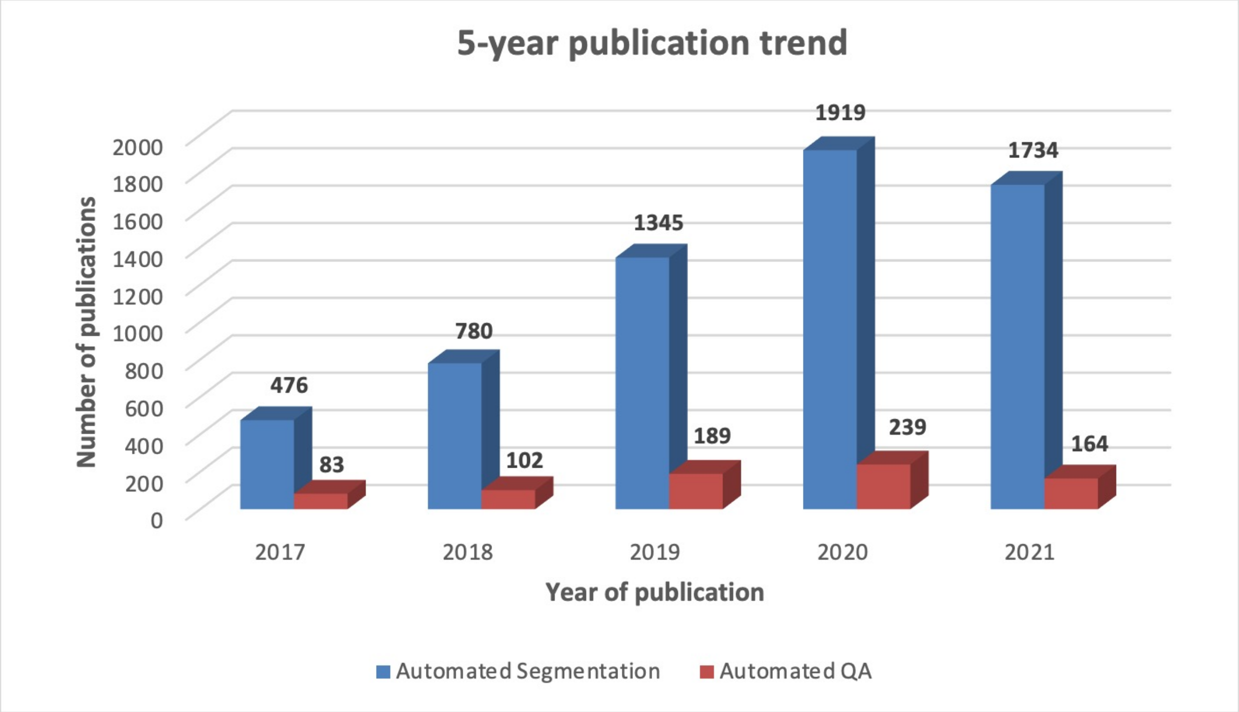
Courtesy A. Sharfo

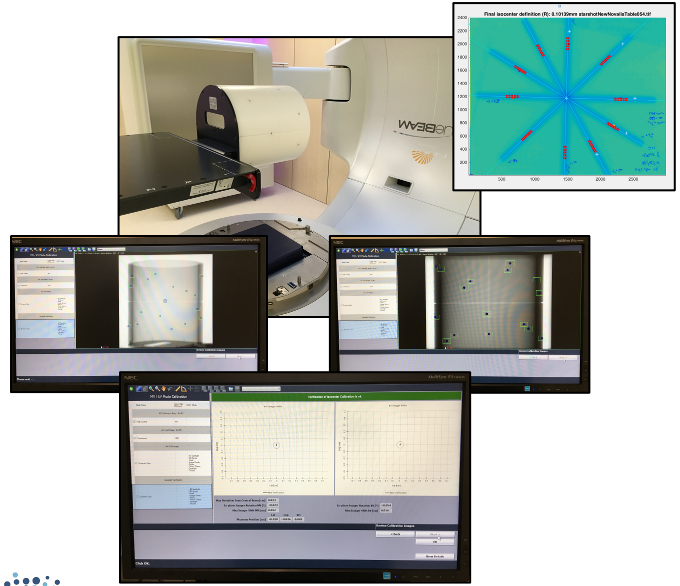
Predictive intelligence in QA



D. Verellen - 2021

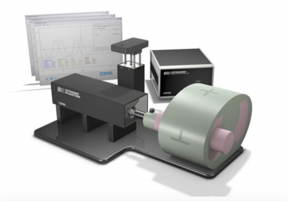
Predictive intelligence in QA

- Machine specific QA



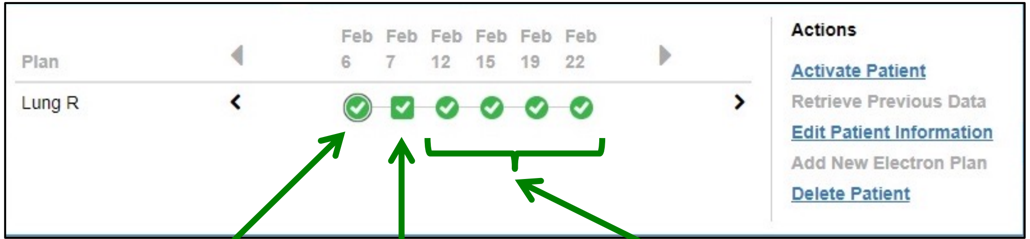
- Patient specific QA
  - Pre-treatment patient specific QA:
    - Assessment of dosimetric accurcy in phantoms or pre-treatment CT
    - IGRT for corrections in patient set-up and motion management
  - *In vivo* dosimetry (IVD):
    - (Residual) set-up errors
    - Intra fraction anatomical variation
    - Linac output errors
    - Planning errors
    - …
  - EPID IVD:
    - 3D dose reconstruction on planning CT and CBCT

QA @ Iridium Network



- **Patient specific QA**
  - QA/QC of the stereotactic unit includes:
    - *Daily QA of output and coincidence of imaging/treatment isocentre,*
    - *Weekly calibration of CBCT and SGRT IGRT components,*
    - *Quarterly E2E testing with dedicated SBRT phantom (thorax phantom, CIRS).*

  - Patient-specific pre-treatment QA and in vivo dosimetry are performed for every patient using the PerFraction platform (Sun Nuclear), which includes:



    - Independent MU calculation,
    - Dose transmission measurements, pre-treatment,
    - Dose transmission measurements, during treatment (in vivo)

QA @ Iridium Network

- **Patient specific QA**

Point Dose

Rel Dose Diff (%)	5
Abs Dose Diff (cGy)	5
Search Radius (mm)	1

2D Analysis

Method	Gamma		
Diff (%)	5	DIST (mm)	2
TH (%)	20	Norm.	Global
Baseline	Fraction 1 (12 feb 2018 13:15)		
Auto Align	Not Available		

3D Analysis

Apply

Diff (%)	5	DIST (mm)	2
TH (%)	20	Norm.	Local
		Pass Tol (%)	95

Image Source

Calculated On: Plan CT

Use expanded dose region when calculating on CBCT image.

Expanded distance (cm) 0

Points | Beams

1RA CW	100,00 %	3.712	0	0	6 MV

DVH

	STRUCTURE NAME	MIN	MAX	MEAN
☑	ChestWall	0,00 Gy	7,97 Gy	1,01 Gy
☑	Esophagus_05	0,01 Gy	1,50 Gy	0,25 Gy
☑	GreatVessels	0,01 Gy	1,84 Gy	0,21 Gy
☑	Heart	0,01 Gy	2,02 Gy	0,17 Gy
☑	Lungs	0,01 Gy	13,75 Gy	0,75 Gy
☑	PTV	10,41 Gy	13,75 Gy	12,74 Gy
☑	SpinalCord_05	0,00 Gy	2,26 Gy	0,18 Gy
☐	BODY	0,00 Gy	13,75 Gy	0,27 Gy

Overall Gamma

PASSING RATE (%)	FAILED (%) LOW	FAILED (%) HIGH	FAILED POINTS LOW	FAILED POINTS HIGH	TOTAL POINTS
98.07%	0,00	1,93	1,0	1.321,0	68.398,0

Delivered ON | Difference ON | Expected ON

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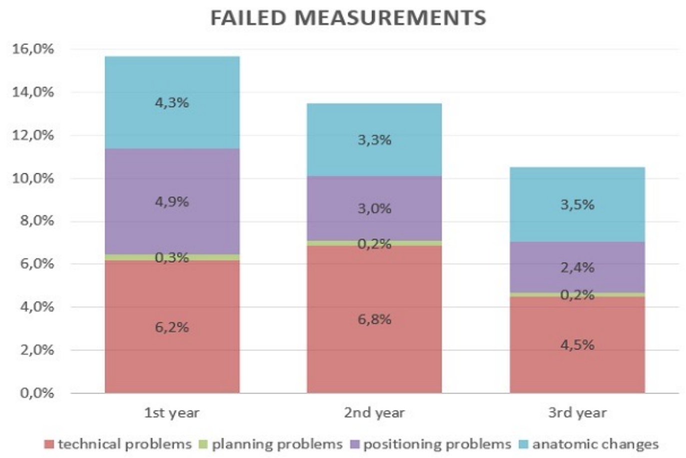
QA @ Iridium Network

- **A retrospective analysis of 63636 EPID IVD measurements on 10652 patients, divided into 3 year-periods (2018 - 2021).**



- Difference between old and new generation treatment machines
- Introduction of SGRT on failures due to positioning
- Introduction of ultra-hypofractionated breast treatment:
  - Failures due to positioning: 5.9% -> 2.6%
  - Failures due to anatomical variation: 1.9% -> 0.2%

- **Transit EPID IVD can be a powerful tool to evaluate and assess possible impact of adaptations to the clinical workflow and a guide for improvements.**

Bossuyt E. *et al.* (Submitted ESTRO2022)

Patient specific QA and AI


Aesop's Fables

- The "Don't cry wolf" problem

  - Automation is nice (needed), but the challenge is finding a good balance between false positive and false negative results

- Don't use universal tolerance levels, rather TL based on centre-specific analysis.

  - Local procedure of patient set-up and immobilization
  - Local treatment technique
  - Local IGRT and motion management procedures
  - …

QA: quality Assurance, TL : Tolerance Levels

Predictive intelligence in QA: an example

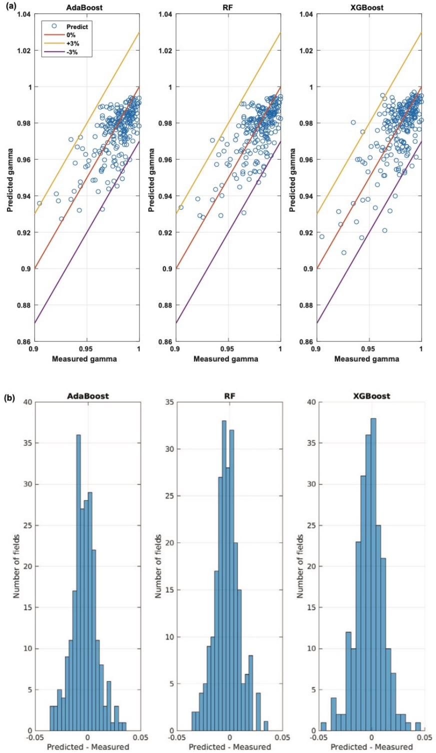


Figure 10.14
IMRT QA portal dosimetry results were analyzed to evaluate how predicted results compared with measured results for the gamma passing rate. From (Lam et al. 2019).

Use a one-class classifier by recognizing that there is one class in the data (say normal perfor- mance), while everything else is considered an outlier or an anomaly

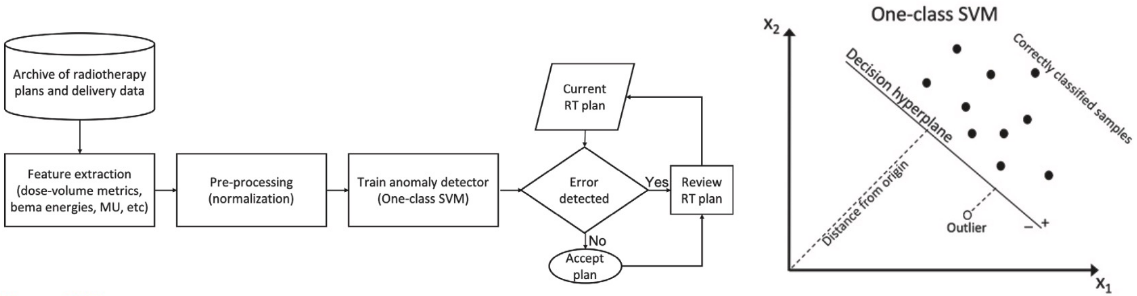


Figure 10.7
An error detection system for radiotherapy. Left: application to RT planning. Right: SVM one-class formalism, where a hyperplane in the feature space [x1, x2] separates correct samples (closed circles) from outliers (open circles) by maximizing distance from the origin.

SVM: support Vector Machine

El Naqa I, *et al.* Machine Learning in RT: What have we learned so far (in The Modern Technology of Radiation Oncology)

Efficiency, Standardization, Quality & Safety

- A huge database and a wealth of information

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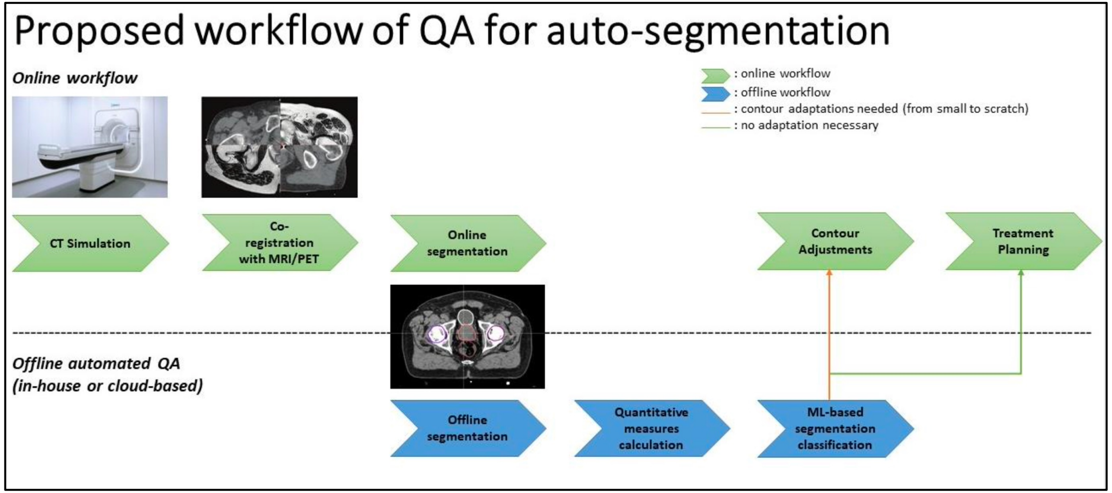
Who's guarding the guardians?

- For treatment planning systems it is custom (compulsary) to perform and independent dose calculation
- What about autosegmentation and autoplanning?



Claessens M, *et al.* Automated detection of online auto-segmentation deviations by use of an independent segmentation algorithm, PMB 2021 (submitted)

Recommendations on implementations and QA

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3rd ESTRO Physics workshop - Science in development

25 October 2019 - 26 October 2019

Budapest, Hungary

For this year the topics offered are:

1. **Computational methods for clinical target volume definition**
   Chairs: Jan Unkelbach & Ben Heijmen
2. **Multi-source data fusion for decision support systems in radiation oncology: opportunities, methodologies, standardizations and clinical translation**
   Chairs: Alberto Traverso & Kathrine Røe Redalen
3. **Implementation/commissioning/QA of artificial intelligence techniques**
   Chairs: Wouter van Elmpt & Dirk Verellen
4. **Clinical applications and quality assurance of surface guided radiation therapy (in collaboration with AAPM)**
   Chairs: Vania Batista & Hania Al-Hallaq
5. **Plan Quality assessment: dose distribution and robustness metrics**
   Chairs: Christian Rønn Hansen & Lamberto Widesott

Radiotherapy and Oncology 153 (2020) 55–66

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journal homepage: www.thegreenjournal.com

ELSEVIER

Review Article

Overview of artificial intelligence-based applications in radiotherapy: Recommendations for implementation and quality assurance

Liesbeth Vandewinckele [a,b,1], Michaël Claessens [c,d,1], Anna Dinkla [e,1,*], Charlotte Brouwer [f], Wouter Crijns [a,b], Dirk Verellen [c,d], Wouter van Elmpt [g]

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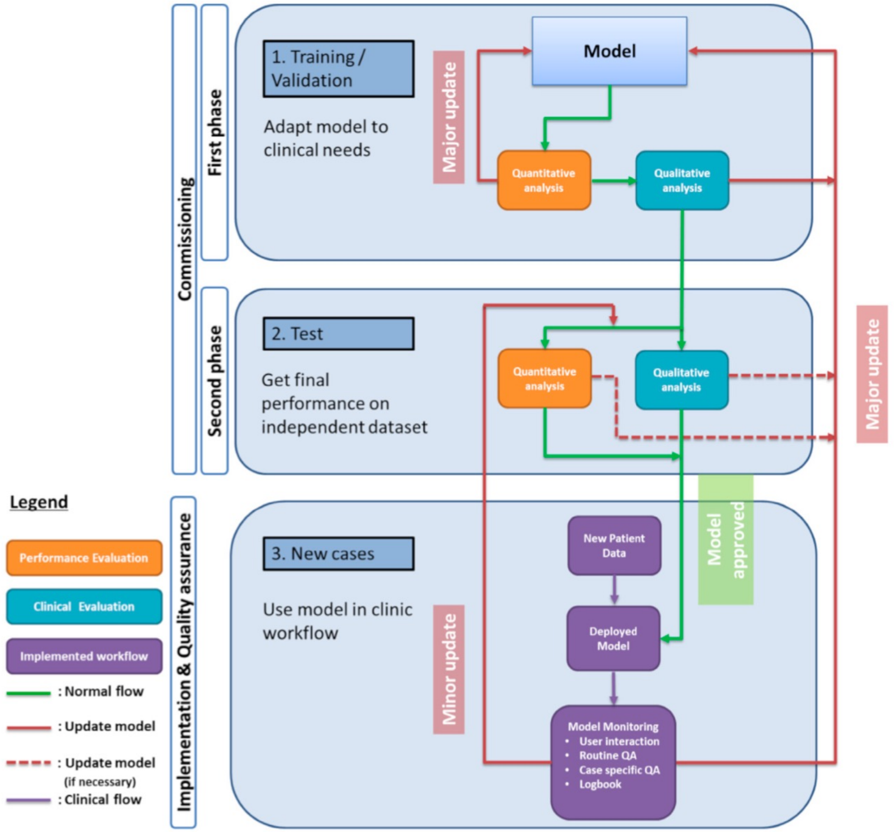
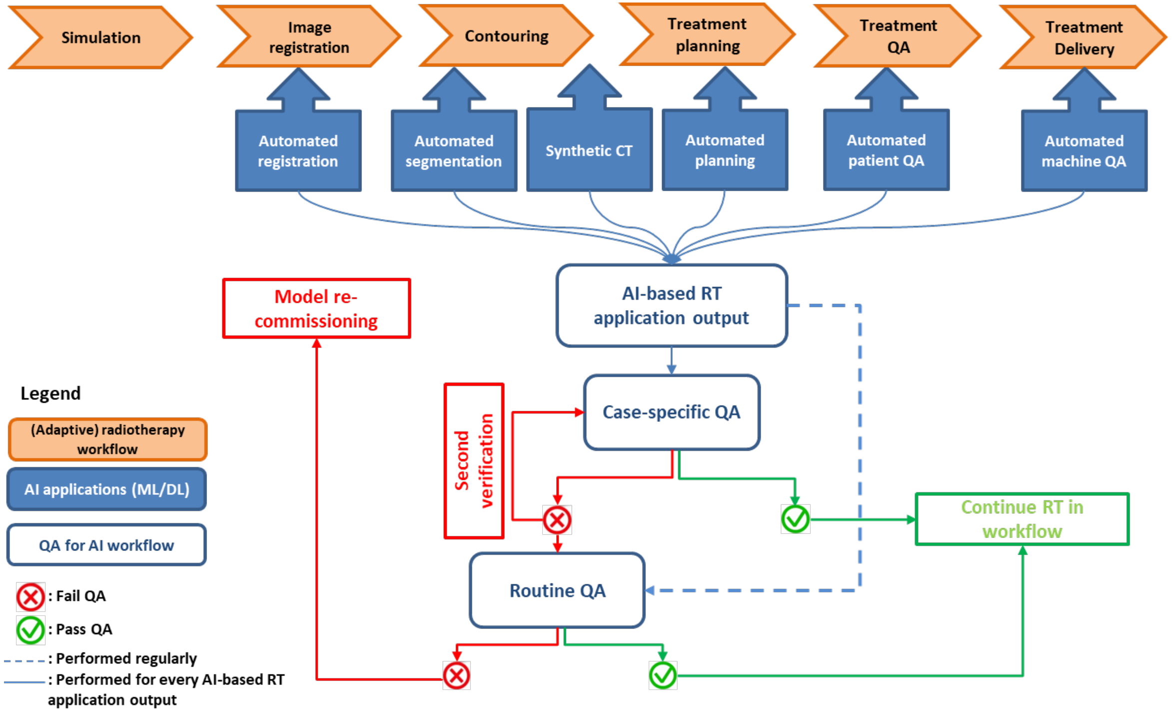
Recommendations on implementations and QA



Recommendations on implementations and QA



Case-specific QA

- Per patient or machine
- Supervision of output
- AI-based QA tools

Routine QA

- Regular supervision
- Monitor for unexpected changes
- Reference test dataset

Claessens M et al. Quality Assurance for AI-based applications in radiation therapy. Seminars in Radiation Oncology, March 2022.

Conclusions

- Machine learning, with its powerful arsenal of data predictive analytics, offers the potential to:
  - allow better **automation of routine** tasks
  - improved **efficiency**
  - enhanced **decision-making** support to the complex processes of treatment planning, quality assurance, and radiation delivery.
  - Improve quality and **increase consistency** in delineation and treatment planning
- AI can amplify detection levels and prediction accuracy of potential failure or **deviation from intent**.
  - Either through machine internal sensors and logs (measuring speeds, positions, rates, etc.) or external devices (measuring dose or surrogates, posi- tions, etc.)
- AI has the potential to foresee stray behaviours with high selectivity allowing efficient **triage for problem solving** as well as **pre-emptive actions**.
  - This will improve machine uptime, reliability

Franquin

There is AI for QA but also QA for AI

Recommended literature

- Vandewinckele L, Claessens M, *et al.* Overview of artificial intelligence-based applications in radiotherapy: Recommendations for implementation and quality assurance. Radiother Oncol 2020; https://doi.org/10.1016/j.radonc.2020.09.008
- Kalet AM, *et al.* Radiation therapy quality assurance tasks and tools: the many roles of machine learning. Med Phys 2020; 47(5): e168-e177
- …