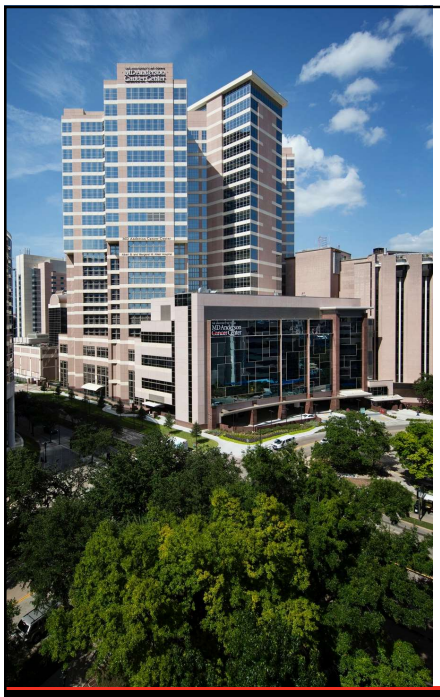


The Value of a Dosimetrist in a Value Based Healthcare Environment

Matthew Palmer, MBA, CMD

THE UNIVERSITY OF TEXAS
MD Anderson Cancer Center
Making Cancer History®

Background

2000 – 2003 Brachytherapy Dosimetry

New Technology Clinical Implementation

2003 – 20010 External Beam Dosimetry

New Technology Product Development

2010 – 2014 Supervisor, Proton Therapy

New Technology Adoption

2014 – 2018 Administration, Development & Operations

Justification of New Technology- Admin, Economics & Policy

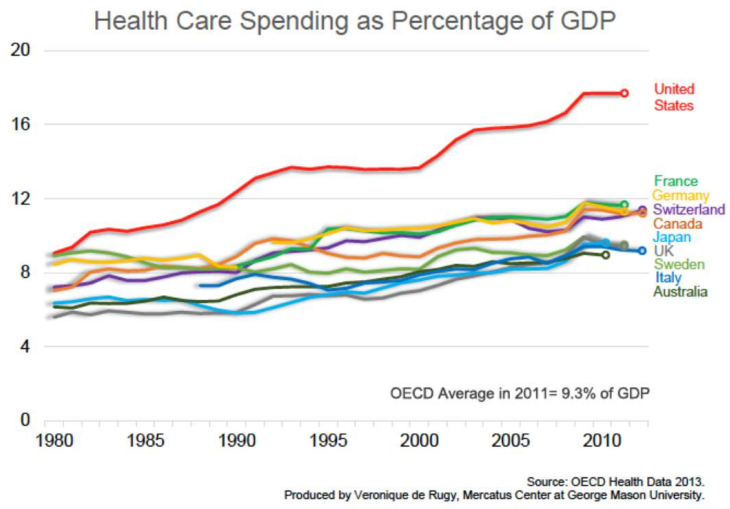
 2

Disclosers

- Co-Patent (Philips): Automatic, Optimal IMRT/VMAT Treatment Planning Software (#9943702) (2018)
- No Financial Benefit

 3

Rising Healthcare Cost



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Healthcare Cost vs. Life Expectancy

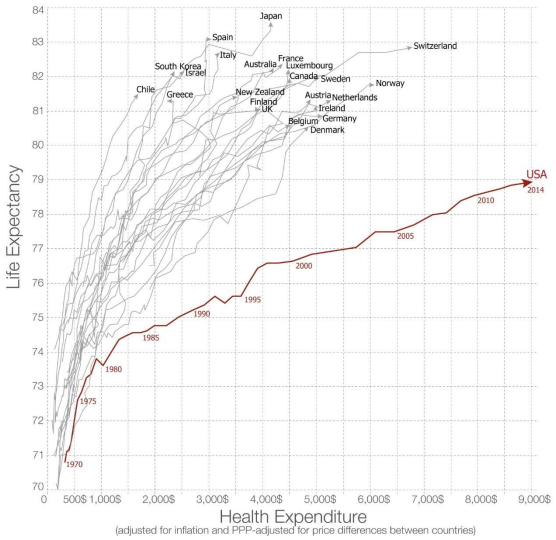

Image Courtesy: https://www.adamtownsend.me/when-healthcare-kills/

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Transition to Value Based Models

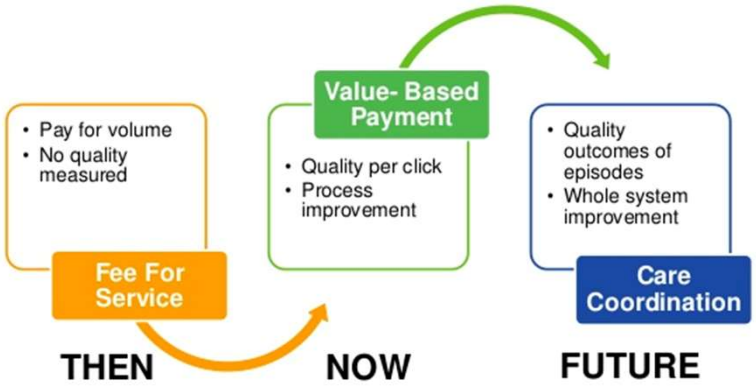

Image Courtesy: https://www.slideshare.net/PYAPC/healthcare-reform-initiatives-affecting-physician-compensation

 6

Fee for Service to Fee for Value

	Fee-for-Volume (Old World)	Fee-for-Value (New World)	
Volume	Providers make money by negotiating higher rates and performing as many services as possible	Providers make money by not only providing services, but other results valued by the industry, such as quality, efficiency, wellness, care coordination, and prevention	Value
Vendors	Payers see providers as vendors	Payers begin to see providers as partners	Partners
Revenue	Providers see every touch as revenue	Providers see every touch as an expense to be managed	Expenses
Provider Based	Most providers have little regard for evidence-based medicine.	Providers care a great deal about evidence based medicine	Evidence Based
Claims	Payers primarily pay providers based on claims	Payers pay providers based on claims plus many other inputs (few of which are automated)	Claims +

Image Courtesy: https://www.slideshare.net/matthijsvanhagen/4-walsteijnedifecs-enabling-value-based-healthcare-2015-04-09-v3/4

 7

Value Based Model – Current Status

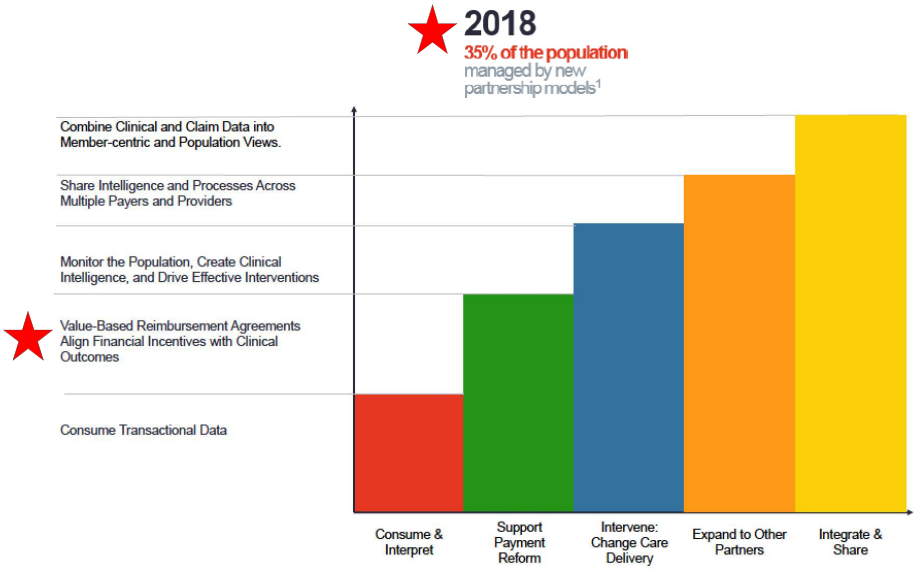

Image Courtesy: https://www.slideshare.net/matthijsvanhagen/4-walsteijnedifecs-enabling-value-based-healthcare-2015-04-09-v3/4

 8

Value Based Model - Provider Risk

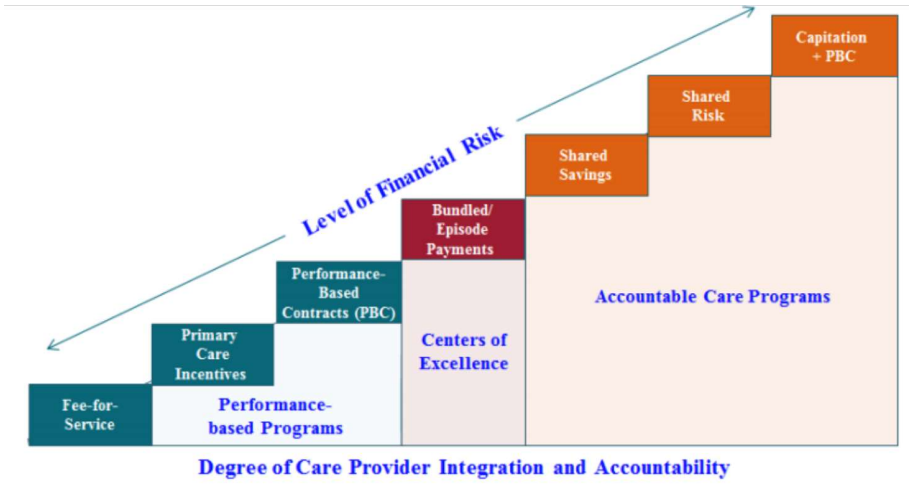

Image Courtesy: http://azpaymentreform.weebly.com/value-based-purchasing-basics.html

 9

"At Risk" Example

Cardiac Catheterization – Fixed Fee + Performance Based Fee that was "at risk" based on the achievement of the following pre-determined metrics

- Employee Satisfaction – 5%
- Patient Satisfaction – 5%
- Quality of Care – 30%
- Cost Reduction – 60%

Image Courtesy: https://www.slideshare.net/PYAPC/healthcare-reform-initiatives-affecting-physician-compensation

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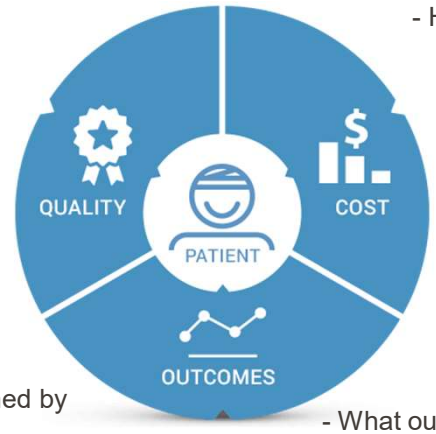
What is Value?

- How is quality defined?
- What metrics are used to define quality?



- How is cost defined?

- How is value defined by the patient?
- How much is the patient willing to pay for value?

- What outcomes are most important?
- What are the parameters of the outcomes?

Image Courtesy: https://global.agfahealthcare.com/main/enterprise-imaging/value-based-healthcare/

 11

Stakeholders' Perspective

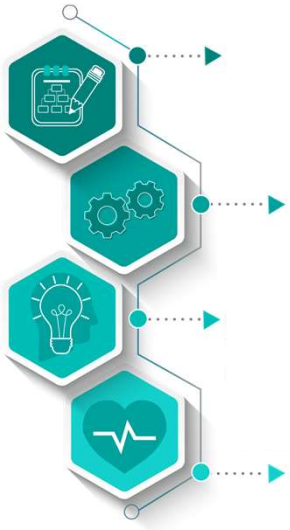


Image Courtesy: https://www.exponent.com/knowledge/alerts/2017/07/value-based-payment-for-medical-devices/

 12

The Value Equation

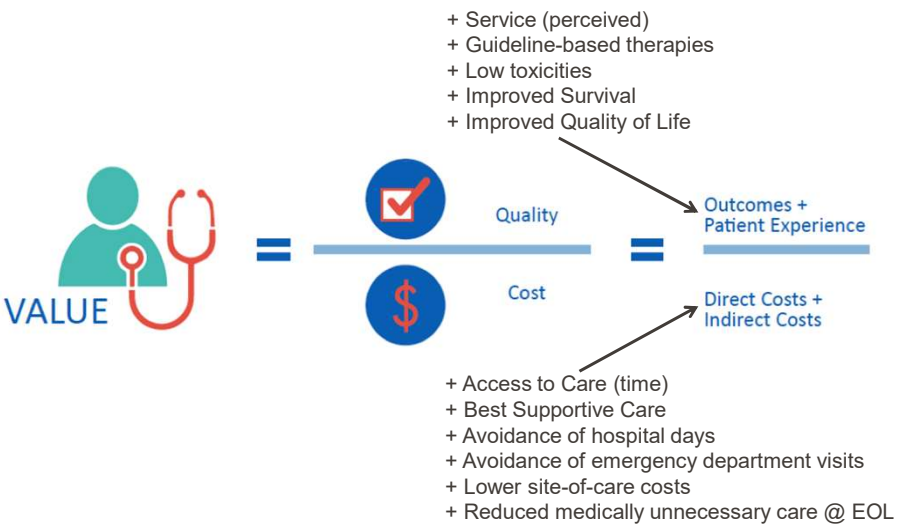


Image Courtesy: http://www.healthcareitnews.com/sponsored-content/solving-healthcare-value-equation-0

 13

Cancer's Impact on Employers

Direct Costs

- Escalating cancer care expenditures

Indirect Costs

- Absenteeism
- Presenteeism
- Caregiver burden / reduced productivity

Survivorship Costs

- Increase in cancer survival rates
- Increase in healthcare utilization during treatment & follow-up
- Maintenance therapy costs

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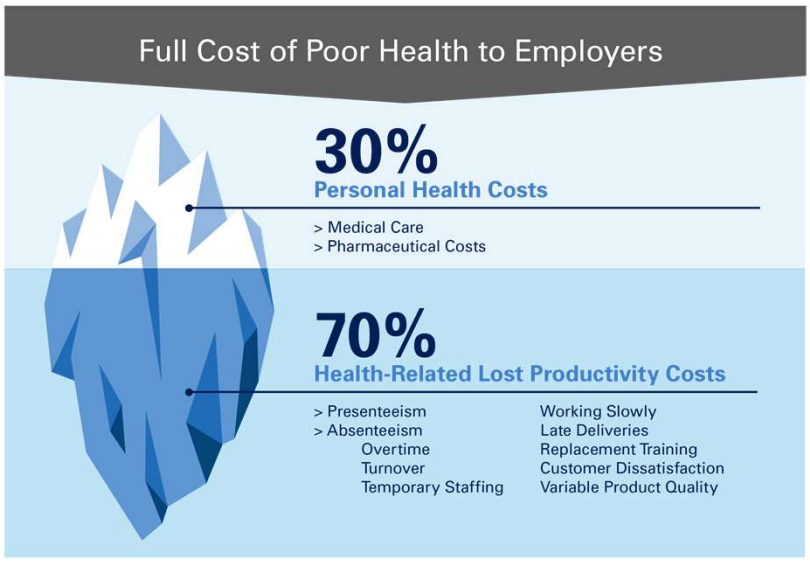
Cancer's Impact on Employers



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Measurement of Value?

1. How do patients know if their healthcare is good care?
2. How do providers pinpoint the steps that need to be improved for better patient outcomes?
3. How do Insurers and employers determine whether they are paying for the best care that science, skill and compassion can provide?
4. How do we figure out which measures can give us the biggest return in better quality of life for patients?
5. Who sets the priorities, and how carries them out?

Source: National Quality Forum

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NATIONAL QUALITY FORUM

1. Process Measures
2. Outcome Measures
3. Patient Experience Measures
4. Infrastructure Measures
5. Composite Performance Measures

Source: National Quality Forum

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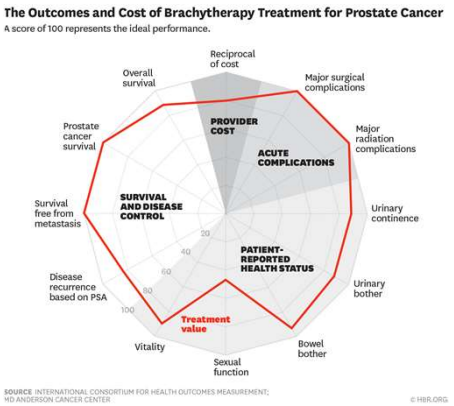
Visualizing Quality



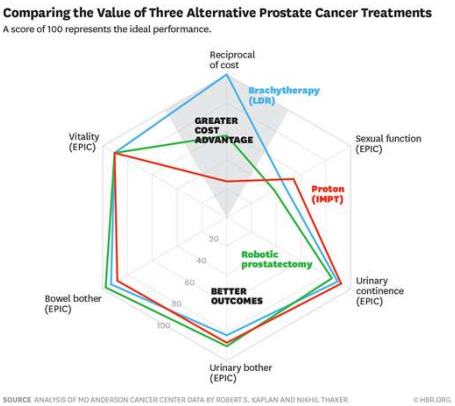


Image Courtesy: https://hbr.org/2015/10/measuring-and-communicating-health-care-value-with-charts

 18

Quality Frameworks

Image Courtesy:

 19

Institute of Medicine (IOM) Framework

1. **Safe:** Avoiding harm to patients.
2. **Effective:** Providing services based on scientific knowledge to all who could benefit.
3. **Patient-centered:** Providing care that is respectful to individual patient preferences needs and values.
4. **Timely:** Reducing waits and sometimes harmful delays.
5. **Efficient:** Avoiding waste, including waste of equipment, supplies, ideas, and energy.
6. **Equitable:** Providing care that does not vary in quality.

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IOM Framework – Radonc Focus

1. **Safe:** Effective Treatment Plans, Achieve dose constraints, ROILS, QA Methods, Toxicity review board
2. **Effective:** Research, Publications, Treatment Planning Development and Improvement
3. **Patient-centered:** Dosimetric plan analysis to determine optimal plan per patient, Plan analysis tools
4. **Timely:** Contouring & Treatment planning time
5. **Efficient:** Operational Process Improvement = Cost reduction
6. **Equitable:** Treatment plan standardization

 21

Safety

Incident Learning

RO-ILS | RADIATION ONCOLOGY® INCIDENT LEARNING SYSTEM
Sponsored by ASTRO and AAPM

- The Patient Safety and Quality Improvement Act of 2005 established essential legal protections in the US to allow for the collection and analysis of medical incidents nationwide.
- RO-ILS is actively collecting, analyzing, and reporting patient safety events.
- Learned experiences from the collected data are used to design systems not only optimized for efficiency but also for error minimization and elimination.

How can/do Dosimetrist Contribute to Radiation Safety?

Safe, Deliverable Plans

Report Errors & Mistakes

Report Often

Education & Training

Implement New Guidelines & Procedures

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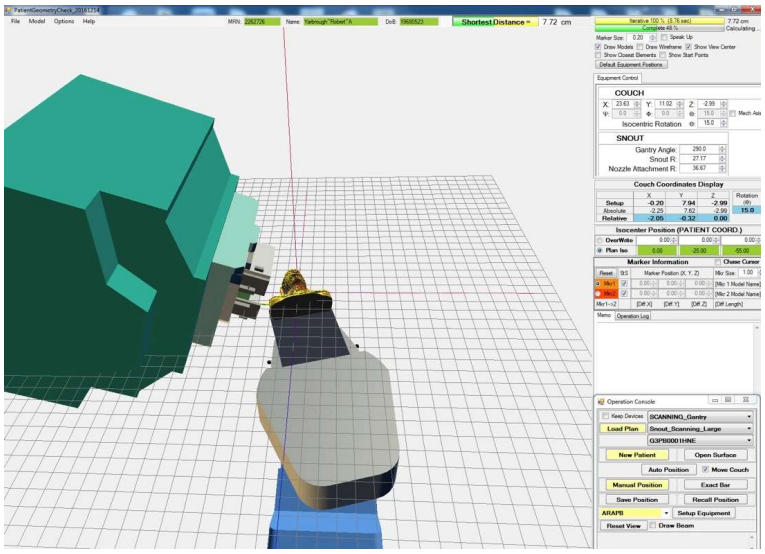
Safety

Dosimetry Operational Recommendation



Goals of Radiation Therapy

1. Maximize disease control
2. Minimize both early and late side effects
3. Preserve organ function
4. Preserve quality of life
5. Minimize extraneous radiation dose to the patient

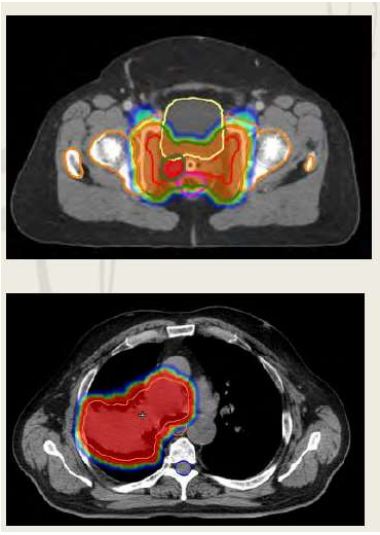
What is an Optimal Plan?

100% of prescribed dose to entire tumor volume and zero dose elsewhere (not attainable).

Physician believes that a better plan exists and that through more effort (and perhaps experience) it can be found

Characteristics of the best "achievable" plan are unknown.

Lack of universally accepted criteria/metrics for defining the "best" plan for each type of cancer.



PlanIQ™, Courtesy of Ben Nelms, PhD

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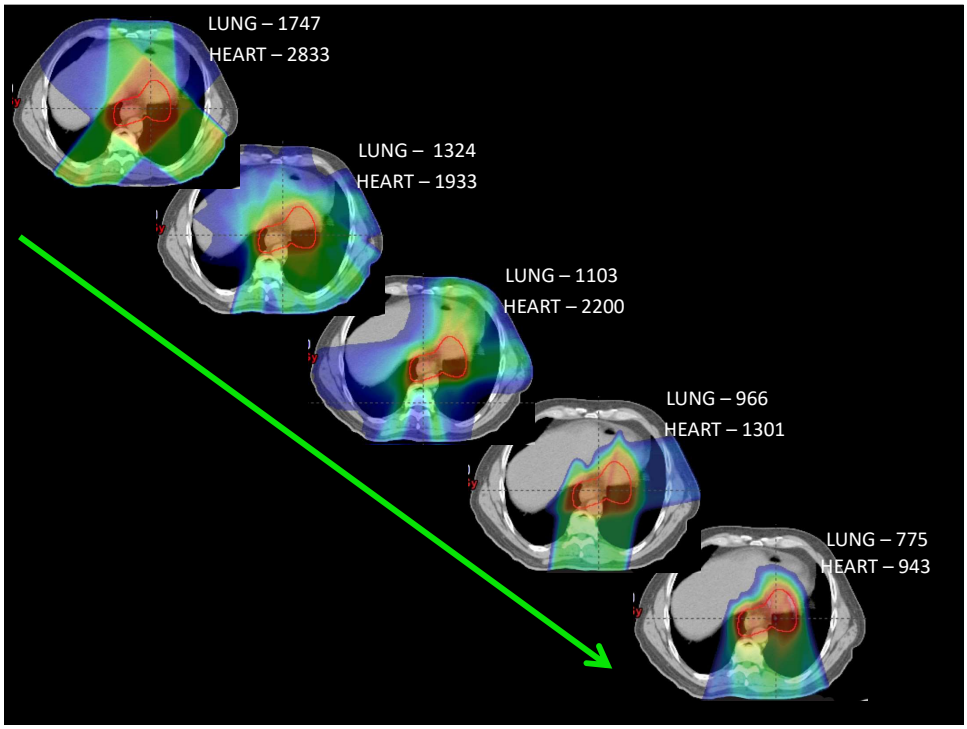

Optimal Treatment Plan?

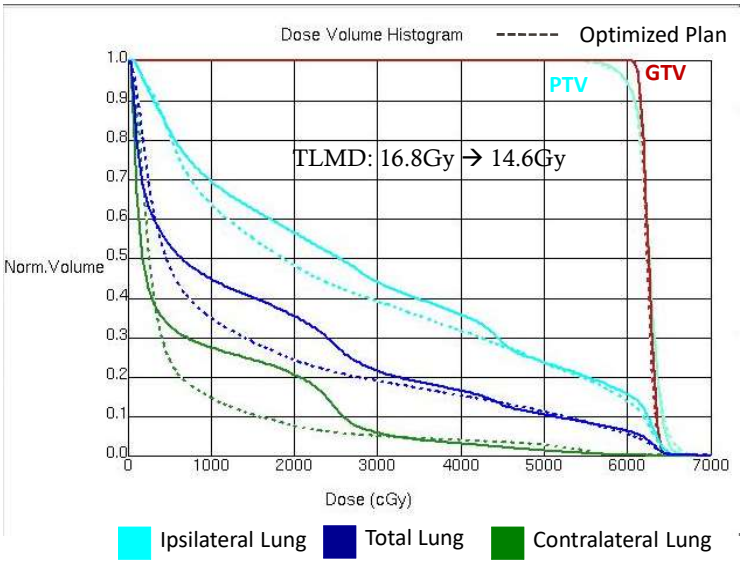

Image Courtesy:

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Limitations of Achieving the Optimal Plan

1. Time, Distance, Shielding
   - Time- Rush to get the patient started
   - Distance- Planner knowledge and experience gap
   - Shielding- Blocked from seeing the optimal plan
1. Lack of established benchmarks
2. Patients uniqueness
3. Disease specific exposure (Recall)
1. Knowledge gap due to advancements in technology

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Effective

Knowledge Based Class Solutions

- Systematic way of applying a technique for a specific site that is consistent, robust and helps produces a clinically acceptable plan more efficiently.

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Effective

Benefits of Class Solutions

- Increase the standard of care for all patients
  - Define an optimal plan by defining benchmarks specific to the clinical site
  - Reducing the significance of disease-specific experiences for IMRT treatment planning
- Elimination of trial-and-error optimization process
  - Reduces the need for experienced based knowledge retrieval
  - More time spent optimizing plan rather than doing plan setup
- More time for advanced optimization
  - Continually improve plans beyond established benchmarks

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Fundamental Principles for Improvement

- All results are determined by inputs with some degree of uncertainty.
- To improve results, you have to *focus on the inputs*, modify them, and control them.
- *Variation is everywhere,* and it degrades consistent, good performance.
- *Valid measurements and data are required* foundations for consistent, breakthrough improvement.
- Only a critical few inputs have significant effect on the output. *Concentrate on the critical few.*

Effective

Modified 6-Sigma- DMAICM

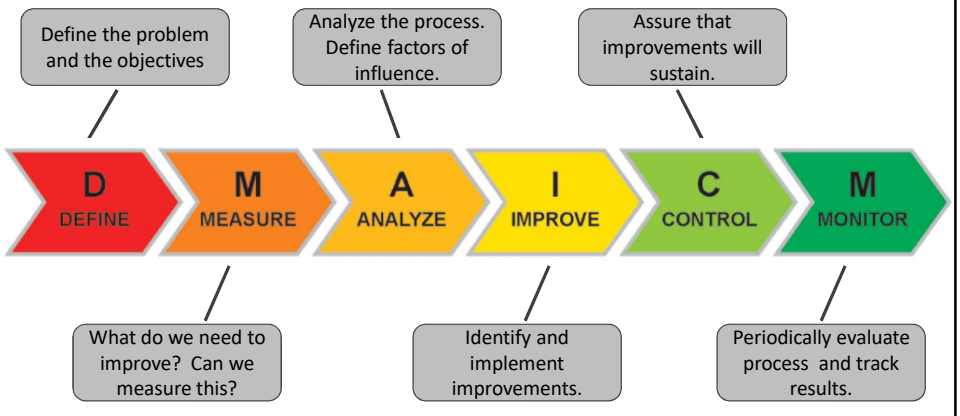
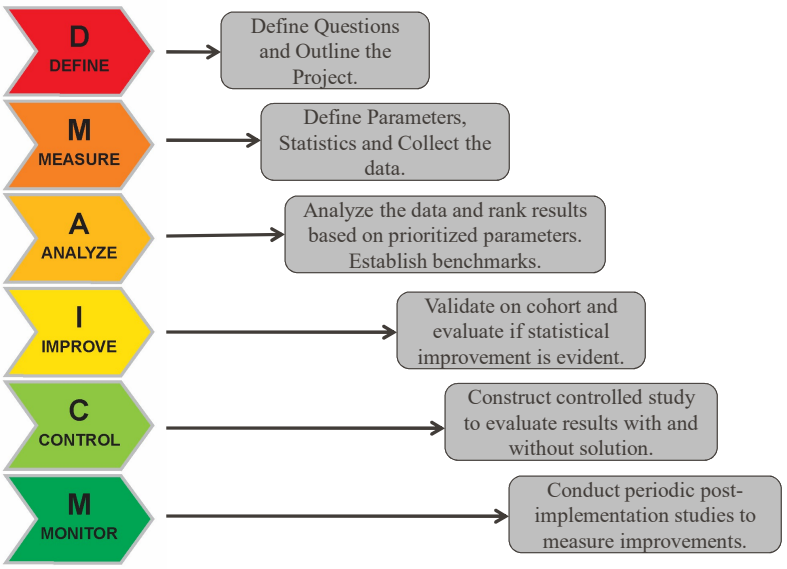


Image Courtesy:

Effective

Class Solution Development



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Effective

Continual Process Improvement

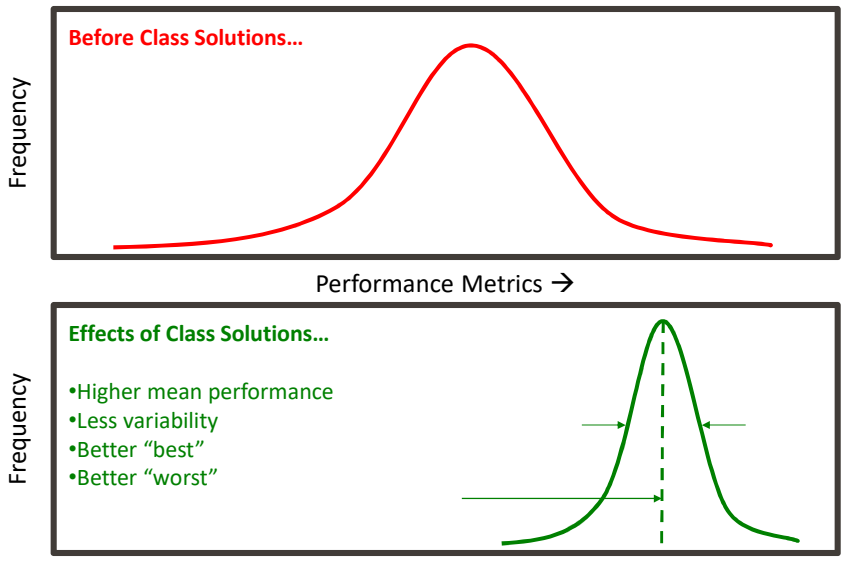

Image Courtesy: Ben Nelms, PhD

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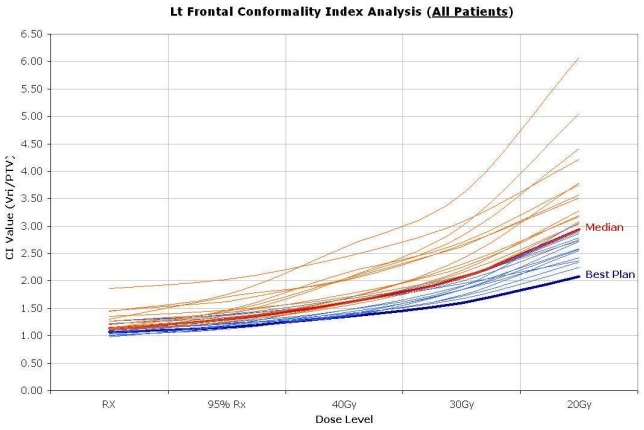
Effective

Treatment Plan Variability



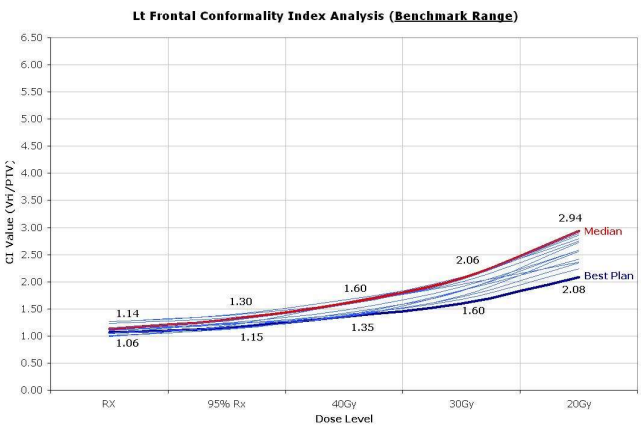
Variability in Conformality Index for 29 patients in the Lt Frontal region for dose ranges from the Rx → 20Gy

Image Courtesy:

 35

Effective

Define Benchmarks for Planning



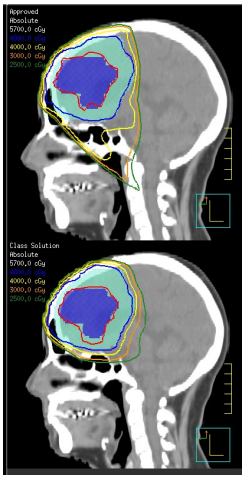


Image Courtesy:

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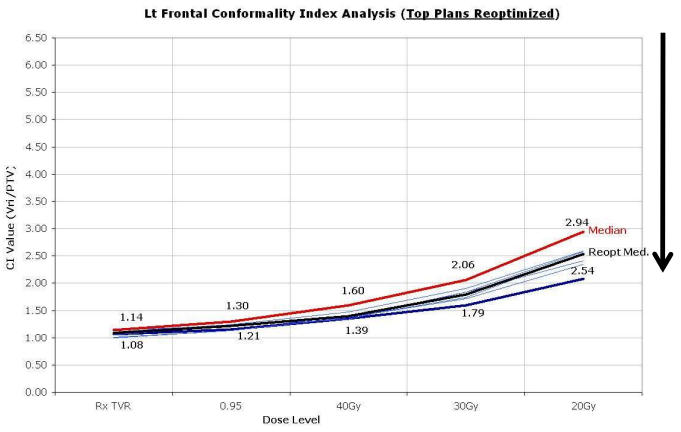
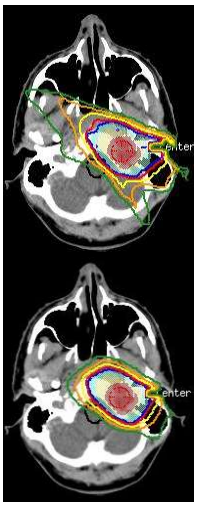
Effective

Standardizing Quality & Variability





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Patient Centered

Identifying Drivers of Quality

Start by identify a patient cohort to analyze, preferably more than 25 patients.

Important to delineate patients with same disease and same characteristics

Good initial evaluation parameters- Prescription and tumor position, Examples…

- *Spine-* Rx, location (c-spine, t-spine, l-spine), tumor shape (horseshoe, paraspinal, donut, question mark)
- *Liver-* Rx, location (lateral, medial, middle)
- *Brain-* Location (right or left), Region (frontal, temporal, etc.)

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Patient Centered

Identifying Drivers of Quality

Ask questions that help define potential statistical relationships, i.e. Geometric and/or Anatomical.

- What are the important anatomical structures?
- Do any anatomical structures impose geometrical limitations?
- What are the difficulties or limitation during optimization?
- What makes one plan different than the other for the same site?

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Patient Centered

Identifying Drivers of Quality

Ask detailed questions that are disease specific:

- Prostate: What is the achievable dose gradient through the rectum?
- Brain: How can we reduce the volume of 30Gy? How can we make the integral dose as conformal as possible? What are the factors that influence the brain mean dose?
- Lung: What is the relationship between the tumor volume and lung volume and are these volumes correlated to the total lung mean dose?
- Esophagus: How do we reduce the heart dose? Does the tumor length impact the lung dose?
- Spine: What is the achievable dose gradient between the CTV and spinal cord?

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Patient Centered

Identifying Drivers of Quality

Are there ways to divide the anatomy or dosimetric relationships into components that help explain the dosimetric results?

- Lung- Uninvolved lung vs. Lung Dose & Lung Involvement vs. Mediastinal Involvement
- Spine- Cord position vs. CTV vs. Achievable dose gradient
- Brain- 30Gy planar symmetry vs. PTV
- Esophagus- Lung Dose vs. PTV border to Carina & Uninvolved Heart vs. Heart Dose.

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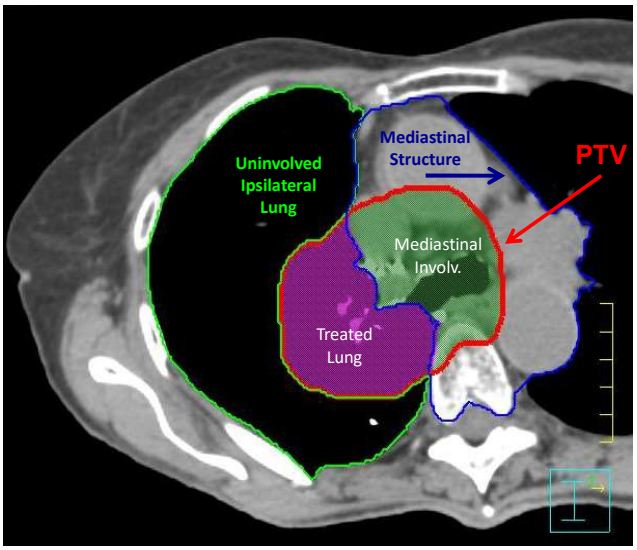
Patient Centered

Lung - % Uninvolved Lung



PTV divided into two components
•Mediastinal Involvement
•Treated Lung

Mediastinal Structure is defined by the tissue in the middle of the lungs and includes the heart, esophagus, major vessels/arteries, anterior vertebral body

Uninvolved Ipsilateral Lung is the amount of lung outside of the PTV

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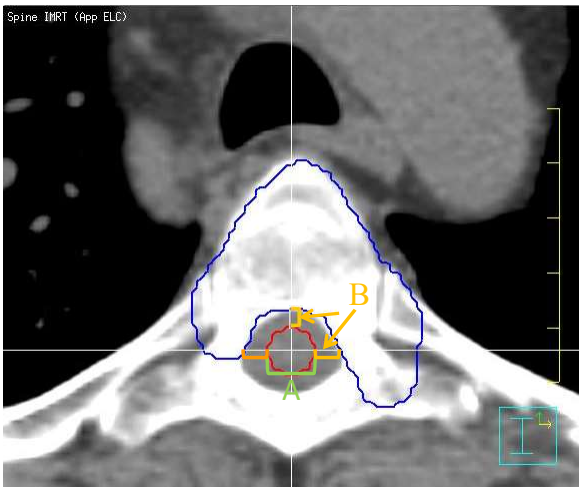
Patient Centered

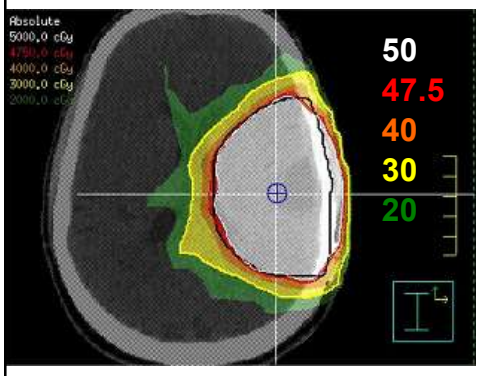
Spine – Achievable Dose Gradient



- A: Spinal Cord Diameter
- B: CTV to Cord distance
- Cord position correlated to % coverage

Patient Centered

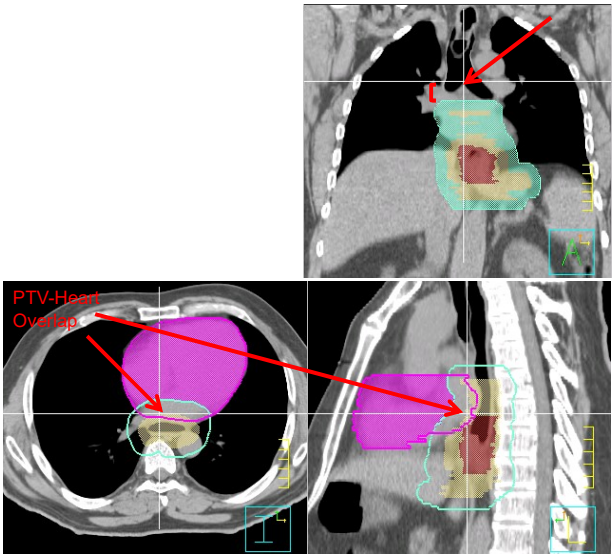
Brain – 3D Planar Measurements



Measure the distance from the PTV Border (Black) and the 30Gy Isodose line (Yellow) in all Planes.

Patient Centered

Esophagus – Distance to Carina



DPC

Find the carina bifurcation.

Count the number of slices between superior border of PTV and carina. (+ inferior/ - superior)

DPC = No. of slices * slice thickness.

%UIH

PTV typically overlaps Heart.

Create a Heart – PTV structure.

%UIH =
(Heart – PTV)/Heart Vol.

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Patient Centered

Patient Specific Benchmarks

Analyze the data and rank results based on prioritized parameters.

- Define benchmarks after data analysis of prioritized statistics.
- Benchmarks will help the treatment planner define if their plan is “optimal”.
- Benchmarks should define the range of achievability.
- Can be segmented based on sub-categories.

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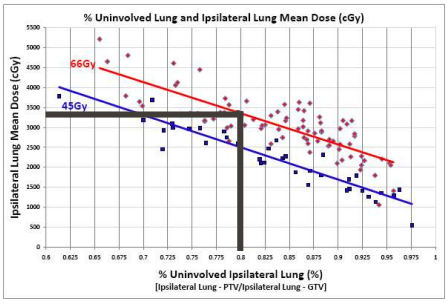
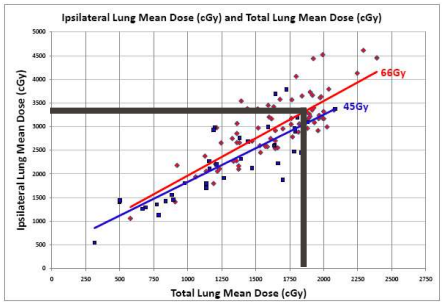
Patient Centered

Lung – Pt. Specific Benchmarks





% UIL correlated with ILMD

The ILMD correlated with TLMD

The ILMD correlated with 5Gy - 30Gy for Ipsi. Lung

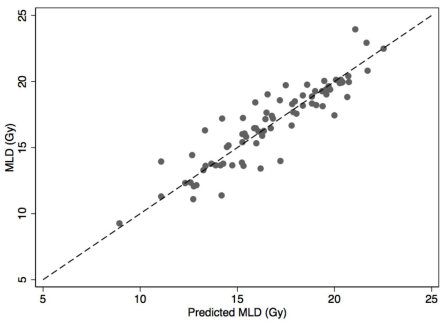
Mediastinal Involvement (ccs) correlated with CLMD

The CLMD correlated with volumes of 5Gy - 20Gy Contra. Lung

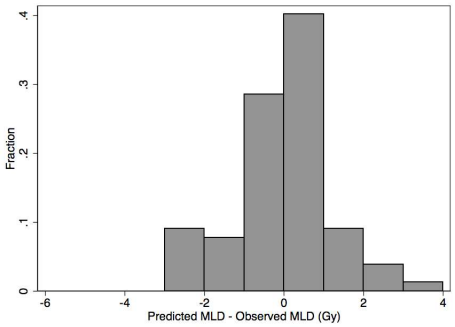
Patient Centered

Lung – Pt. Specific Benchmarks

TLMD = Rx * (1.22 * TxILV)/TLV + ((0.38-0.07 * Superior) - (0.14*Apex))* IL-PTV)/TLV + ((0.437 * (Med/1000)+(0.04 * V_Post)) * CLV)/TLV



Actual MLD (Gy) vs. Predicted MLD (Gy)
Correlation = 0.91, p-value < 0.001



Predicted MLD – Observed MLD (Gy)
Break down of absolute differences

Patient Centered

Lung – Pt. Specific Benchmarks

Prescription (cGy)	7000
PTV Volume	190
Inferior/Superior*	Superior
Apex (Y/N)*	N
Anterior/Posterior/Posterior CW*	Posterior
Ipsilateral Lung Volume	2463.2
Uninvolved Ipsalateral Lung	2355.3
Contralateral Lung Volume	2562.6
Total Lung Volume	5025.8
Lung Involvement	125.5
Mediastinal Involvement	64.2

Notes: Insert Values into Yellow Boxes
*Input names exactly as written in column C
Superior = Middle of PTV Sup. to the bottom of T6 vert. body
Apex = Superior Sulcus with CW involvement
Posterior CW = Post. Lesions abutting Vert. Body

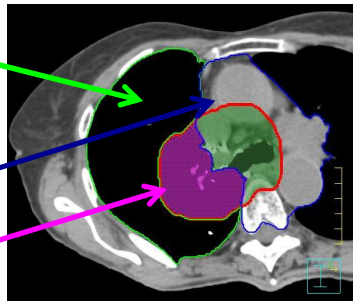
Ipsilateral Lung - PTV

% Uninvolved Lung- (Ipsilat. Lung-PTV)/Ipsilat. Lung Vol.
PTV- Mediastinal Structure

Uninvolved Ipsilateral Lung
(Ipsilateral Lung – PTV)

Mediastinal Structure

Lung Involvement/Treated Lung
(PTV – Mediastinal Structure)



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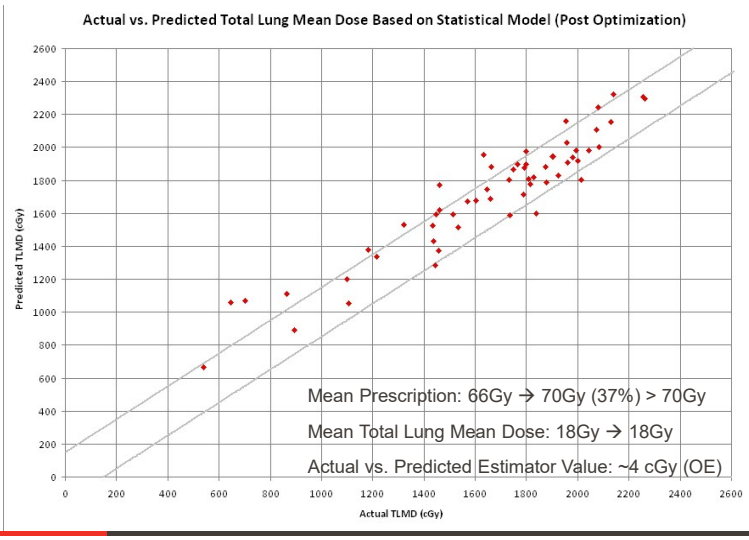
Patient Centered

Lung – Pt. Specific Benchmarks

IMRT Lung Estimator Statistical Model Validation

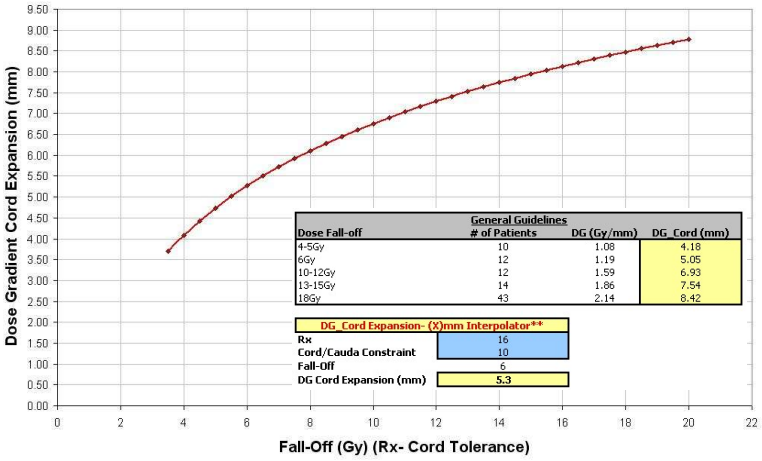


 50

Patient Centered

Spine – Pt. Specific Benchmarks

DG_Cord_Exp (mm) based on Dose Fall-off (Gy) (Rx- Cord Tolerance)



General Guidelines			
Dose Fall-off	# of Patients	DG (Gy/mm)	DG_Cord (mm)
4-5Gy	10	1.08	4.18
6Gy	12	1.19	5.05
10-12Gy	12	1.59	6.93
13-15Gy	14	1.86	7.54
18Gy	43	2.14	8.42

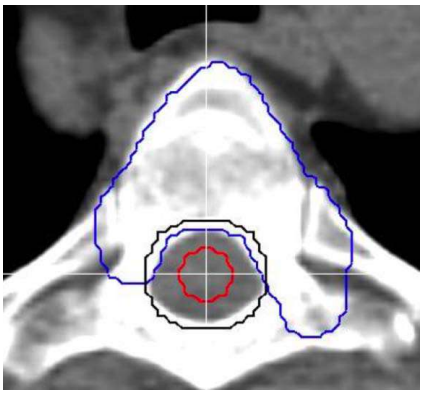
DG_Cord Expansion- (X)mm Interpolator**	
Rx	16
Cord/Cauda Constraint	10
Fall-Off	6
DG Cord Expansion (mm)	5.3

 51

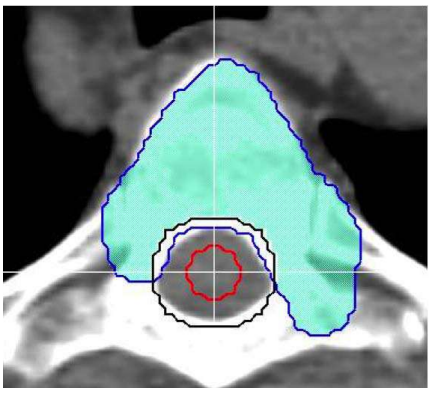
Patient Centered

Spine – Pt. Specific Benchmarks

Dose Gradient Cord



pCTV based on DG_Cord



Planning CTV (pCTV) = CTV – DG_Cord

pCTV Goal: > 97% coverage

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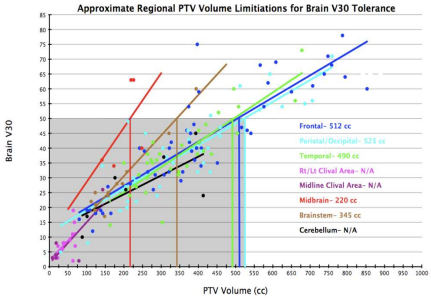
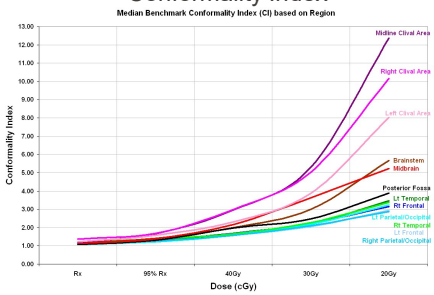
Patient Centered

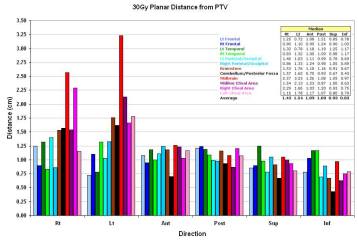
Brain – Pt. Specific Benchmarks

Brain V30%



Conformality Index



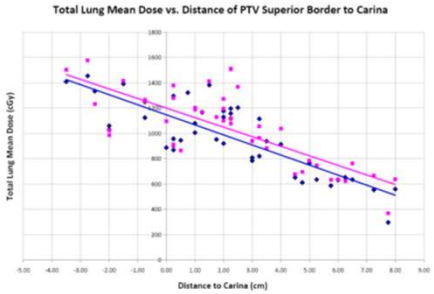


3D Planar Measurements

Patient Centered

Esophagus – Pt. Specific Benchmarks

DPC (cm) & TLMD (cGy)



%UIH (%) & Heart Mean Dose (cGy)

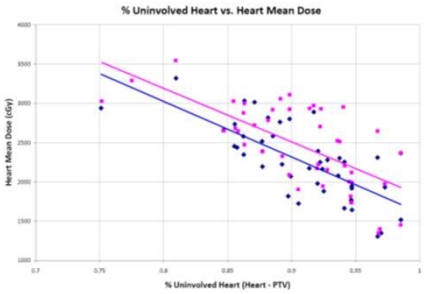


Image Courtesy:

Patient Centered

Esophagus – Pt. Specific Benchmarks

Esophagus IMRT: Heart and Lung Objective Estimator Spreadsheet

Prescription (cGy)	5040	**Notes:**	Insert Values into Yellow Boxes
PTV Volume	825.0		
Distance from PTV to Carina (cm)	-2.5	Reference Superior Slice of PTV: Inferior "+" & Superior "-"	
Heart Volume	693.0		
Uninvolved Heart Volume	640.0	Heart - PTV	
% Uninvolved Heart (%UIH)	0.92		

		Estimated Lung Volumes (%)		
		V5 %	V10 %	V20 %
Estimated Total Lung Mean Dose (TLMD)	1345.9	69.1%	43.7%	24.7%
Actual Total Lung Doses				

		Estimated Heart Volumes (%)		
		V30 %	V40 %	V50 %
Estimated Heart Mean Dose (HMD)	2161.6	24.7%	14.0%	7.0%
Actual Heart Doses				

Image Courtesy:

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Equitable

Standardized Treatment Planning

Validate the consistency and robustness of the class solutions.

- Validate on cohort and evaluate if statistical improvement and consistency is evident.
- If the results are statistically better and robust from patient to patient, then the class solutions are finalized.
- Evaluating the effectiveness and efficiency of the class solutions in a clinical setting.
- 8-10 dosimetrist and physicist with varying degrees of experience planned 3 cases with and without the class solutions.
- Evaluated years of experience vs. plan quality and treatment planning time for each plan.

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Equitable

Lung – Class Solution

	Guideline	IMRT Objectives	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
Rt Lung												
Rt Anterior	Anterior Location w/ out extension into posterior lung	Obj. #1 or Obj. #2**	030-030	330-330	000-000	350-300	000-270	000-250	000-230	000-210		
Rt Posterior	Posterior loction w/out significant Mediastinal Involvement	Obj. #1 or Obj. #2**	000-310	000-280	000-250	000-230	000-210	000-180	000-160	000-140		
Rt Peripheral	< 100 cc Mediastinal Involvement	Obs. #3	030-030	330-330	000-000	350-300	000-270	000-240	000-220	000-200		
Rt General	> 100 cc Mediastinal Involvement, Midline, or Complicated Tumor Shape	Obs. #1 or Obs. #2**	030-030	330-330	000-000	350-300	000-270	000-240	000-220	000-200	000-170	
Lt Lung												
Lt Anterior	Anterior Location w/ out extension into posterior lung	Obj. #4 or Obj. #5**	330-330	030-030	000-000	010-060	000-090	000-110	000-130	000-150		
Lt Posterior	Posterior loction w/out significant Mediastinal Involvement	Obs. #4 or Obs. #5**	000-050	000-080	000-110	000-130	000-150	000-180	000-200	000-220		
Lt Peripheral	< 100 cc Mediastinal Involvement	Obs. #6	330-330	030-030	000-000	010-060	000-090	000-120	000-140	000-160		
Lt General	> 100 cc Mediastinal Involvement, Midline, or Complicated Tumor Shape	Obs. #4 or Obs. #5**	330-330	030-030	000-000	010-060	000-090	000-120	000-140	000-160	000-190	

***Note: Obj. #2 & #5- SIB*

Structures Needed for Mean Lung Dose and Lung Objective Estimator Spreadsheet

fsMediastinum	Contour Mediastinum: Slice Range of PTV: Include Heart, Descending Aorta, & Anterior of Vertebral Body	+Tip: Contour every other slice and interpolate
fsLungInvolvement^^	PTV - Mediastinum	*Note: PTV minus "Lung Involvement" = Mediastinal Involvement
fsUninvolvedLung^^	Ipsilateral Lung - PTV	*Note: Calculates % Uninvolved Lung

^^Note: Record Volumes

Volumes Needed for Mean Lung Dose and Lung Objective Estimator Spreadsheet

Ipsilateral Lung Volume	
fsUninvolvedLung	*Ipsilateral Lung - PTV
Contralateral Lung Volume	
fsLungInvolvement	*PTV - Mediastinum

IMRT Objectives #1 (Rt Lung): PTV = 60Gy - 70Gy

Planning Structures

Structure	*Expansion/Contraction Guidelines*
fsptvexp10mm	PTV + 10mm
fsptvring	fsptvexp10mm - PTV
fsexternal	External contours slice range of PTV
fsntavoid	external - fsptvexp10mm

Objectives

Structure	*Objective*	*Dose*	*%*	*Weight*
PTV	Min Dose	Rx		100
PTV	Uniform Dose	Rx*1.015		100
PTV	Max DVH	Rx*1.06	0	100
Cord	Max Dose	4000		60
fsntavoid	Max DVH	5500	0	20
fsntavoid	Max DVH	3500	4	20
fsntavoid	Max DVH	3000	8	20
fsptvring	Max DVH	Rx		10
Rt Lung (Ipsilateral Lung)	Max DVH	500	##	10
Rt Lung (Ipsilateral Lung)	Max DVH	1000	##	10
Rt Lung (Ipsilateral Lung)	Max DVH	2000	##	10
Rt Lung (Ipsilateral Lung)	Max DVH	3000	##	10
Lt Lung (Contralateral Lung)	Max DVH	500	##	10
Lt Lung (Contralateral Lung)	Max DVH	1000	##	10
Lt Lung (Contralateral Lung)	Max DVH	2000	##	10

Note: Reference Mean Lung Dose and Lung Objective Estimator Spreadsheet

***Notes structures should be named exactly like the nomenclature above because the Hotscripts will depend on "exact" and "consistent" nomenclature**

Image Courtesy:

 57

Equitable

Lung – Class Solution Impact

Photons

Lung Estimator Highlighted cases that were not fully optimized

Reoptimized all of the cases

Data was significantly more consistent

Average TLMD: 1817 → 1690 (-127)

Protons

		Original @ 74 CGE			Reoptimized @ 74 CGE			Difference		
		TLMD	ILMD	CLMD	TLMD	ILMD	CLMD	TLMD	ILMD	CLD
8	LIA	1218	2709	2	913	2127	1	-305	-583	-1
11	LIP	866	2064	0	780	1860	0	-86	-204	0
8	LSA	1147	2658	55	1016	2279	98	-131	-379	43
14	LSP	1150	2876	82	1089	2599	24	-61	-276	-58
4	RIA	1871	3155	249	1490	2597	246	-381	-558	-3
9	RIP	1599	2738	4	1204	2478	3	-395	-260	-1
18	RSA	1630	3015	133	1424	2604	124	-206	-411	-9
17	RSP	1290	2547	33	1186	2191	14	-104	-356	-19
89	Mean	1346	2720	70	1138	2342	64	-209	-378	-6

TLMD: -209 cGy
ILMD: -378 cGy
CLMD: -6 cGy

Image Courtesy:

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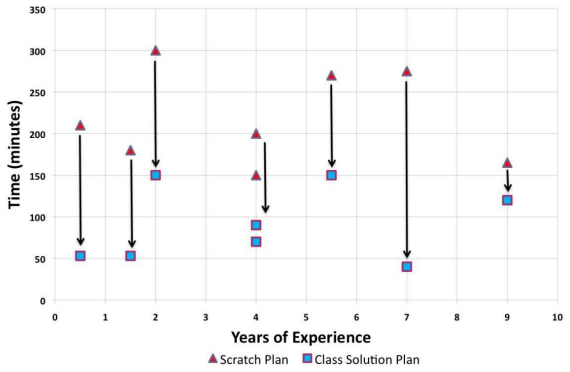
Equitable

Spine – Class Solution Impact



Avg. Time Reduction = -128.2 minutes

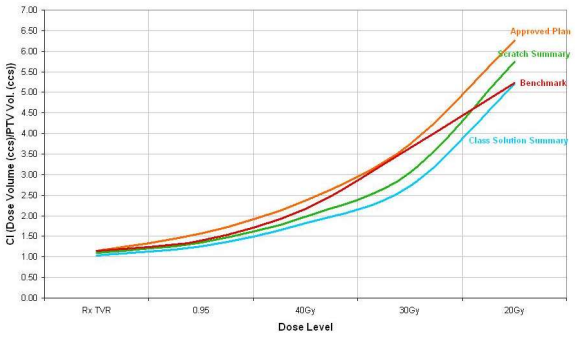
		Tx Plan Time	Total Mus	% Cov. (100% Rx Line)	% Max Dose	CTV Min Dose (cGy)	Ant. DG (mm)	Rt DG (mm)	Lt DG (mm)
T-Spine	Indept. Plan	214	8284	92.8%	117.0%	1157	2.00	4.44	2.72
	pCTV Plan	85	6582	97.8%	115.3%	1294	1.86	3.32	2.40
		-128	**-1703**	**5.0%**	**-1.7%**	**137**	**-0.14**	**-1.12**	**-0.32**
	T-Test (<0.05)	*2E-05*	*0.004*	*0.108*	*0.609*	*0.058*	*0.408*	*0.004*	*0.202*

Avg. MU Reduction = - 1703 MUs = - 2.8 minutes

Equitable

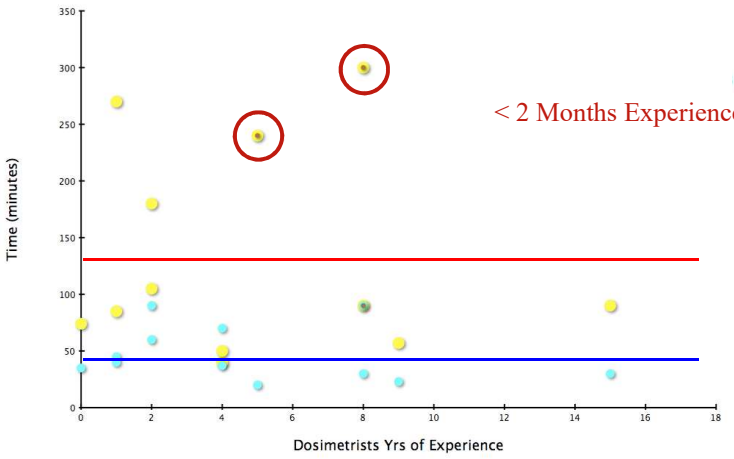
Brain – Class Solution Impact

	#	Vol. (cc)	30Gy Vol. (cm^3)*	Brain (V30)	Brain (Mean)
Frontal					
Historical Benchmark	55	380	35.39	41%	3043
No Class Solution (NCS)	8	360	43.96	43%	2957
Class Solution (CS)	8	371	22.00	36%	2684
(NCS- CS)		**-11**	**21.96**	**7%**	**273**
Parietal/Occipital					
Historical Benchmark	38	391	36.76	41%	2727
No Class Solution (NCS)	8	392	32.61	43%	2985
Class Solution (CS)	7	343	19.10	36%	2653
(NCS- CS)		**49**	**13.51**	**7%**	**332**
Temporal					
Historical Benchmark	34	347	40.45	40%	2923
No Class Solution (NCS)	9	437	49.42	47%	3355
Class Solution (CS)	10	383	23.57	39%	2988
(NCS- CS)		**54**	**25.85**	**8%**	**367**
Brainstem					
Historical Benchmark	13	194	50.93	27%	2138
Class Solution	5	285	46.48	29%	2172
(HB- CS)		**-91**	**4.45**	**-2%**	**-34**



Equitable

Brain – Class Solution Impact



	L Eye	L ON	R Eye	R ON	OC	BS Max	Brain Mn	Brain V30	Plan Time
					Midbrain				
Scratch Plan	392	1703	350	1416	4727	5353	2321	30.0%	132
Class Solution Plan	215	1665	139	1397	4374	5313	2374	26.3%	48

-64%

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Equitable

Esophagus – Class Solution Impact

- Cohort of patients randomly selected from clinical database
- Reoptimized blindly with class solutions, benchmark calculator, and objectives
- Compared Clinical Plans to Class Solution Plan

Total Lung		**Heart**		**Liver**	
Mean:	-134 cGy	Mean:	-81 cGy	Mean:	-751 cGy
V5:	-0%	V20:	-2.3%	V30:	-6.3%
V10:	-4%	V30:	-2.6%	V40:	-1.4%
V20:	-5.8%	V40:	-2.6%		

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Equitable

Continual Improvement

Conduct periodic post-implementation studies to measure effectiveness of class solutions.

- Evaluate patients that were treated with or without the class solutions after implementation.
- Periodically evaluate to see if benchmarks and or solutions need to be readdressed and/or improved.
- Investigate the clinical impact, ie dose escalation, survival, toxicity reduction.

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Equitable

Lung – Grade 3 Pneumonitis

- Evaluation of Treatment-related Pneumonitis Advanced Stage NSCLC
- 151 Patients
- Median Dose- 63Gy
- Rate of Grade ≥ 3 TRP [3D-CRT- 32%, **IMRT- 8%]**

- New Study: 7 (8%) patients of 84 had Grade ≥ 3 Pneumonitis
- Lung Mean Dose Estimator used to to analyze plan quality
- Plans reoptimized to see if suggested objectives could be met
- Dose statistics reviewed for these patients

MDACC, IJROBP, Vol. 68, No. 1, pp. 94-1267102, 2007

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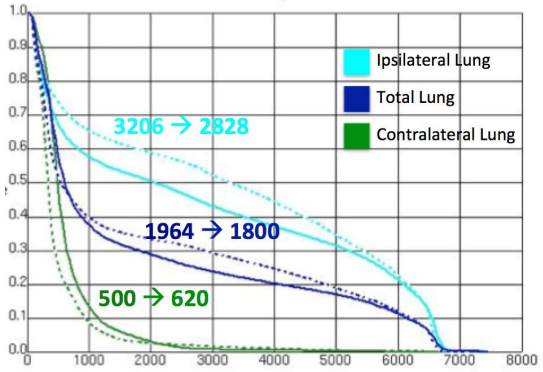
Equitable

Lung – Grade 3 Pneumonitis

		Estimated Lung Volumes (%) V5 %	V10 %	V20 %	V30 %
Estimated Ipsilateral Lung Mean Dose based on data	2454.9	62	53	43	36
Actual Ipsilateral Lung Mean Dose	2840.0	82	67	50	39
Estimated Contralateral Lung Mean Dose	391.3	19	7	2	
Actual Contralateral Lung Mean Dose	520.0	26	9	4	
Estimated Total Lung Mean Dose	1578.1	44	33	26	21
Actual Total Lung Mean Dose	1853.0	59	42	30	24

+275



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Equitable

Lung – Grade 3 Pneumonitis

Grade > 3 Pneumonitis Patients	Total Lung - GTV								Isilateral Lung					
	TLMD	ILMD	CLMD	V5	V10	V15	V20	V25	V30	V5	V10	V15	V20	V25	V30
Original Plans (Total)	1876	3679	466	49	41	37	34	30	26	89	82	76	69	63	57
Reoptimized Plans (Total)	1705	3328	455	50	35	30	27	25	23	86	75	63	58	56	54
Difference	171	352	11	0	6	7	6	5	4	3	7	12	11	7	3
Average % Change	9.1%	9.6%	2.4%	-0.6%	15.0%	18.2%	19.3%	17.9%	13.5%	3.6%	8.3%	16.0%	16.2%	10.9%	5.0%

Potentially link between sub-optimal plans and G ≥ 3 Pneumonitis?

Average drop in ILMD -331 (Pop.: 85)

5 of the 7 had the largest drop in IL V_{20}: -11% (Pop.: - 1.9%)

Other 2 patients had IL Vol. (cc) of 1013 & 1091 (Pop.: 1460)

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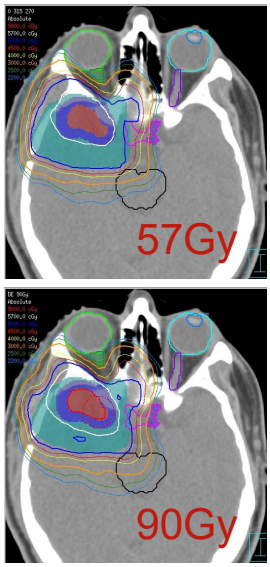
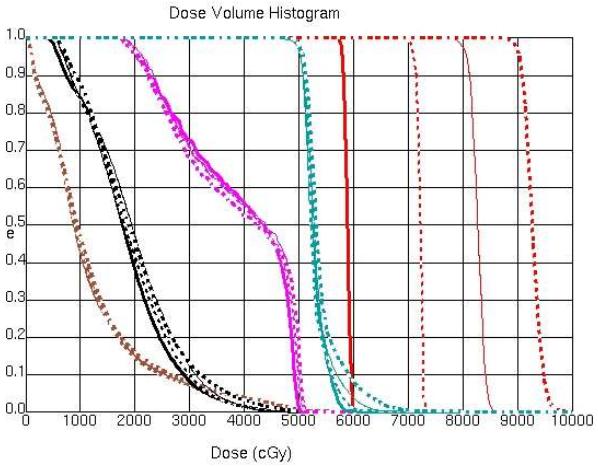
Equitable

Brain – Dose Escalation





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Equitable

Esophagus – Dose Escalation

MDACC Patterns of Failure Study

- 15/66 (23%) pts failed in GTV
- 2/66 (3%) pts failed in CTV without GTV
- 1/66 (1.5%) pts failed in PTV only
- 4/66 (6%) pts failed outside PTV as site of first failure alone
- 2/66 (3%) failed outside PTV simultaneously with in-field failure.
- No patients failed in non-targeted esophagus
- Median dose at site of failure: 5250cGy

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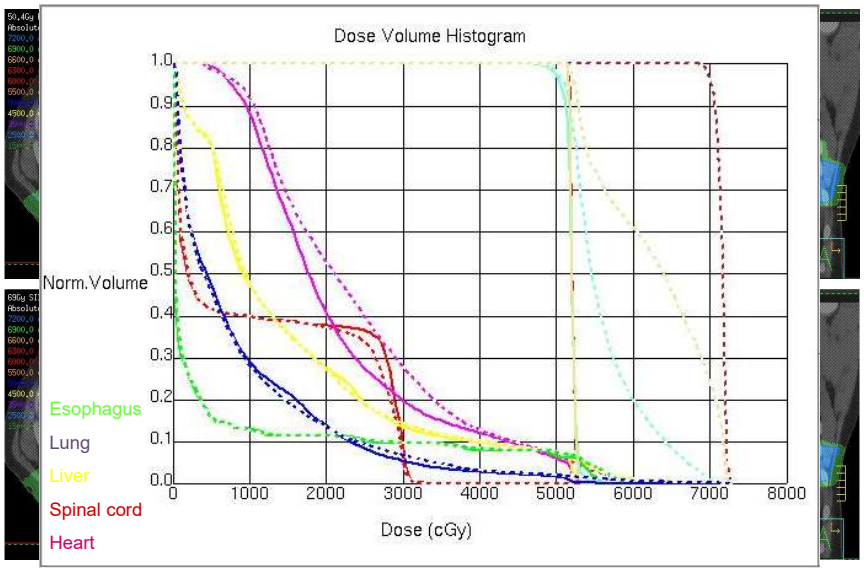
Equitable

Esophagus – Dose Escalation



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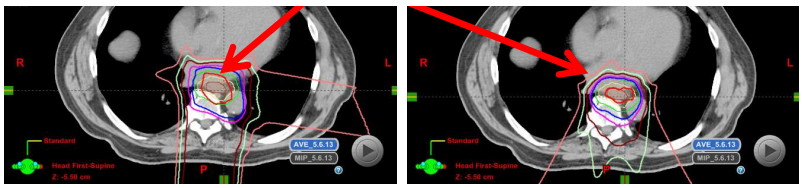
Equitable

Esophagus – Dose Escalation

IMRT- SIB VMAT- SIB

	IMRT-SIB	VMAT- SIB	PSPT-IB	IMPT- SIB
Liver Mean	769	704	53	48
Heart Mean	1948	1839	1157	741
Total Lung Mean	825	788	488	295



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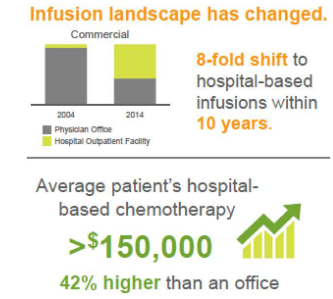
Summary

1. **Safe:** Knowledge and Experience to to design safe, effective, and deliverable treatment plans thus reducing toxicities and treatment errors.
2. **Effective:** Intimate knowledge of treatment planning challenges are key for driving improvement in quality.
3. **Patient-centered:** Utilization of patient specific constraints are key for developing personalized optimal plans.
4. **Equitable:** Benchmarks and Metrics with standardized class solutions shift treatment planning focus to optimization, i.e. beating the benchmarks.
5. **Timely:**
6. **Efficient:**

Healthcare Disruptors

1. Genetics & Gene Therapies
   - Liquid Biopsies
   - CAR T-cell therapy
   - CRISPER
2. Shifts in Site of Care
3. Artificial Intelligence (AI)



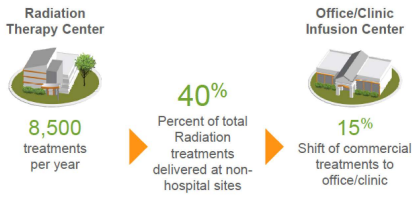


Image Courtesy: SG2, SROA Meeting, 2017

Emerging AI in Healthcare

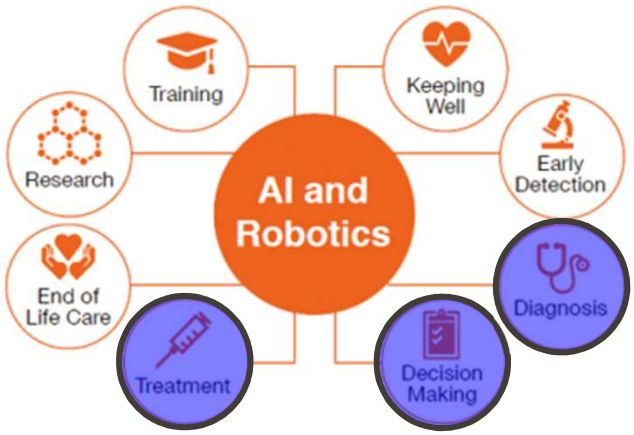


Image Courtesy:

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Timely

Emerging AI in Radiation Oncology

1. Has not been fully exploited due to technical hurdles and hardware limitations in the past.
2. Increasing and promising applications of machine learning algorithms involving big data in Radiation Oncology due to recent developments in computer technology.
3. Goal is to expand personalized radiotherapy worldwide.

Reference: Frontiers, April 2018

Source: https://www.frontiersin.org/research-topics/6126/machine-learning-with-radiation-oncology-big-data

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Timely

Emerging AI in Radiation Oncology

Big Data in Radiation Oncology may include:

- Radiomics and quantitative imaging
- Knowledge-based treatment planning
- Treatment response prediction via machine learning
- Clinical decision support via machine learning
- Comparative effectiveness research in radiation oncology
- Bioinformatics for improved quality of care
- Motion compensation and correction via machine learning
- Automated image registration and contouring
- Radiogenomics
- TCP and NTCP modeling
- Cancer registries and classification
- Tracking big organ dose data for patient safety in radiation therapy
- Machine learning models for early cancer prediction and prevention
- Natural language processing of EMR data

Source: https://www.frontiersin.org/research-topics/6126/machine-learning-with-radiation-oncology-big-data

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Timely

Emerging AI in Radiation Oncology

Big Data in Radiation Oncology may include:

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Source: https://www.frontiersin.org/research-topics/6126/machine-learning-with-radiation-oncology-big-data

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Timely

Radonc Vendors – Auto-planning Tools

Pinnacle³ Auto-Planning
Accelerated IMRT therapy & VMAT planning

IMRT Planning is often a labor-intensive process, generating inconsistent results and delaying the start of treatment. The process is tedious and repetitive, requiring significant planner/physician interaction. Plan quality varies depending on the experience of the user, creating inconsistencies in treatment. Pinnacle³ Auto-Planning makes this entire process faster, less labor intensive and more reproducible.

RaySearch Laboratories — PRODUCTS SERVICES CAREER

Automatic plan generation

Plan explorer is based on the capability to automatically generate a large number of treatment plans for defined clinical goals and combinations of treatment techniques and machines. It also provides efficient means to filter and browse among plan candidates to find the most desired one.

varian — ONCOLOGY PROTON THERAPY ABOUT VARIAN

CREATE HIGH QUALITY PLANS QUICKLY & EFFICIENTLY.

RapidPlan Knowledge-Based Planning

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RTOG® RADIATION THERAPY ONCOLOGY GROUP

Class Solution IMRT Planning, Blinded Comparison to the RTOG 0539 Cohort

A. Mahajan,[1] D. Manfredi,[2] C. L. Rogers,[3] M. Palmer,[1] E. Hillebrandt,[1] S. Bilton,[1] R. Yoder,[4] G. Robinson,[4] K. Velasco,[4] M. Mehta,[5]

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This project was supported by RTOG grant U10 CA21661, and CCOP grant U10 CA37422 from the National Cancer Institute (NCI). The publication's contents are solely the responsibility of the authors and do not necessarily represent the official views of the National Cancer Institute.

1. In this study we compared individually-generated IMRT plans from RTOG 0539 to Automated Class Solution plans, blindly created for the same cohort.
2. We used multi-criteria (MCA) plan quality metrics for plan assessment and comparison approved by consensus by all MDs.
3. A total of 86 (45 Group II, 41 Group III) planning CT scans and associated ROI's were imported.
4. The CS plans were generated by 3 dosimetrists in an average of 27.8 minutes per plan to obtain a clinically acceptable plan that complied to protocol requirements.

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Plan Quality Metric Component	Result	Score	Max Score	Performance
[PTV_5400] V[54.0Gy] (%)			37.50	
[PTV_5400] Min dose (Gy)			22.50	
[PTV_5400] D[0.03cc] (Gy)			7.50	
[PTV_5400] Conformation Number [51.3Gy]			15.00	
[PTV_5400] Homogeneity Index [54.0Gy]			5.00	
[PTV_5400] Inhomogeneity Index			5.00	
Global Max Location (ROI)			7.50	
[LENS_L] D[0.03cc] (Gy)			5.00	
[LENS_R] D[0.03cc] (Gy)			5.00	
[RETINA_L] D[0.03cc] (Gy)			5.00	
[RETINA_R] D[0.03cc] (Gy)			5.00	
[OPTIC_NRV_L] D[0.03cc] (Gy)			5.00	
[OPTIC_NRV_R] D[0.03cc] (Gy)			5.00	
[CHIASM] D[0.03cc] (Gy)			0.00	
[BRAIN_STEM] D[0.03cc] (Gy)			0.00	
[BRAIN- GTV] V[30.0Gy] (%)			5.00	
[BRAIN- GTV] Mean dose (Gy)			5.00	
[PTV_5400] Conformality Index [30.0Gy]			5.00	
[PTV_5400] Conformality Index [20.0Gy]			5.00	
Total [19 Metrics]		**0.00 ***	**150.00**	**0.0% ***

Plan Quality Metric Component	Result	Score	Max Score	Performance
[PTV_6000] V[62.0Gy] (%)			20.00	
[PTV_6000] Min dose (Gy)			12.50	
[PTV_6000] D[0.03cc] (Gy)			4.50	
[PTV_6000] Homogeneity Index [60.0Gy]			2.50	
[PTV_6000] Inhomogeneity Index			2.50	
[PTV_5400] V[54.0Gy] (%)			17.50	
[PTV_5400] Min dose (Gy)			10.00	
[PTV_5400] D[0.03cc] (Gy)			3.00	
[PTV_5400] Conformation Number [51.3Gy]			7.50	
[PTV_5400] Homogeneity Index [54.0Gy]			2.50	
[PTV_5400] Inhomogeneity Index			2.50	
Global Max Location (ROI)			7.50	
[LENS_L] D[0.03cc] (Gy)			5.00	
[LENS_R] D[0.03cc] (Gy)			5.00	
[RETINA_L] D[0.03cc] (Gy)			5.00	
[RETINA_R] D[0.03cc] (Gy)			5.00	
[OPTIC_NRV_L] D[0.03cc] (Gy)			5.00	
[OPTIC_NRV_R] D[0.03cc] (Gy)			5.00	
[CHIASM] D[0.03cc] (Gy)			0.00	
[BRAIN_STEM] D[0.03cc] (Gy)			0.00	
[BRAIN- GTV] V[30.0Gy] (%)			5.00	
[BRAIN- GTV] Mean dose (Gy)			5.00	
[PTV_5400] Conformality Index [30.0Gy]			5.00	
[PTV_5400] Conformality Index [20.0Gy]			5.00	
[PTV_6000] Conformation Number [57.0Gy]			7.50	
Total [25 Metrics]		**0.00 ***	**150.00**	**0.0%**

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		COHORT II DOSIMETRIC RESULTS							COHORT II PLAN METRIC RESULTS			
		CLASS SOLUTION			RTOG							
Metric	Constraint	AVERAGE [range]		Violations	AVERAGE [range]		Violations	p-value	MAX SCORE	CLASS SOLUTION SCORE	RTOG SCORE	p-value
[PTV_5400] V[54.0Gy] (%)	≥ 95	96.0	[82.1 - 99.9]	5	93.8	[33.6 - 99.9]	4	0.30	30	28.9	23.4	0.04^
[PTV_5400] Min dose (Gy)	≥ 51	50.3	[40.6 - 53.9]	5	51.3	[35.1 - 53.8]	1	0.14	16	13.3	13.1	0.83
[PTV_5400] D[0.03cc] (Gy)	≤ 60	59.3	[57.5 - 64.3]	1	58.0	[53.9 - 61.2]	0	0.00*	5.5	5.5	5.4	0.25
[PTV_5400] Conformation Number [51.3Gy]	> 0.5	0.70	[0.483 - 0.820]	2	0.64	[0.371 - 0.839]	2	0.00^	14	10.2	6.4	0.00^
[PTV_5400] Homogeneity Index [54.0Gy]	< 0.25	0.10	[0.055 - 0.368]	1	0.08	[0.025 - 0.192]	0	0.26	4	2.9	2.9	0.50
Global Max Location (ROI)	w/in PTV_5400			3			11	n/a	4.5	4.2	2.7	0.00^
[LENS_L] D[0.03cc] (Gy)	< 5	1.2	[0.0 - 3.6]	0	2.6	[0.0 - 16.5]	7	0.00^	2	1.6	1.3	0.00^
[LENS_R] D[0.03cc] (Gy)	< 5	1.3	[0.0 - 4.8]	0	2.4	[0.0 - 12.2]	3	0.00^	2	1.6	1.3	0.01^
[RETINA_L] D[0.03cc] (Gy)	< 45	10.7	[0.2 - 43.3]	0	11.7	[0.2 - 42.2]	0	0.30	4.5	3.5	3.4	0.43
[RETINA_L] Mean dose (Gy)	< 30	4.8	[0.1 - 23.8]	0	6.0	[0.1 - 27.6]	0	0.06	4.5	4.1	4.0	0.07
[RETINA_R] D[0.03cc] (Gy)	< 45	8.9	[0.3 - 48.8]	1	10.8	[0.1 - 46.3]	1	0.07	4.5	3.7	3.5	0.08
[RETINA_R] Mean dose (Gy)	< 30	4.3	[0.2 - 29.2]	0	5.5	[0.1 - 26.8]	0	0.02^	4.5	4.2	4.0	0.06
[OPTIC_NRV_L] D[0.03cc] (Gy)#	≤ 50	20.2	[0.0 - 49.0]	0	21.7	[0.0 - 55.0]	15	0.13	5.5	5.5	0.0#(6)	0.01^
[OPTIC_NRV_L] Mean dose (Gy)	< 40	15.6	[0.0 - 46.4]	4	15.6	[0.0 - 51.9]	6	0.71	5.5	3.8	4.0	0.62
[OPTIC_NRV_R] D[0.03cc] (Gy)#	≤ 50	17.8	[0.4 - 49.8]	0	20.8	[0.2 - 54.3]	5	0.00^	5.5	5.5	0.0#(5)	0.02^
[OPTIC_NRV_R] Mean dose (Gy)	< 40	12.4	[0.3 - 45.5]	2	14.4	[0.2 - 49.6]	4	0.00^	5.5	4.3	4.2	0.23
[CHIASM] D[0.03cc] (Gy)#	≤ 54	24.9	[0.0 - 53.6]	0	26.7	[0.4 - 55.6]	1	0.09	3	3.0	0.0#(1)	0.32
[CHIASM] Mean dose (Gy)	< 40	22.0	[0.0 - 52.5]	14	23.7	[0.3 - 53.3]	15	0.04^	5.5	3.3	3.4	0.83
[BRAIN_STEM] D[0.03cc] (Gy)#	≤ 55	27.8	[2.2 - 54.8]	0	30.1	[0.5 - 58.5]	4	0.06	2	2.0	0.0#(3)	0.08
[BRAIN_STEM] Mean dose (Gy)	< 40	17.9	[1.1 - 47.4]	9	18.3	[0.3 - 53.2]	8	0.31	2.5	1.7	1.8	0.31
[BRAIN- GTV] V[30.0Gy] (%)	< 50	15.6	[5.9 - 29.0]	0	18.5	[5.6 - 39.7]	0	0.00^	4	3.1	2.9	0.05^
[BRAIN- GTV] Mean dose (Gy)	< 30	14.4	[4.7 - 22.7]	0	15.4	[7.2 - 24.4]	0	0.03^	4.5	2.8	2.7	0.32
[PTV_5400_EVAL] Conformality Index [30.0Gy]	< 6	2.9	[2.0 - 5.5]	0	3.5	[2.0 - 5.6]	0	0.00^	6	4.6	3.7	0.00^
[PTV_5400_EVAL] Conformality Index [20.0Gy]	< 6	4.8	[2.7 - 10.2]	9	5.5	[2.7 - 10.1]	17	0.00^	4.5	2.5	1.6	0.00^
Avg. Total Metric Results (minus 18 patients with CT calculation issues)@									150	132.9	94.7	0.00^
Avg. Total Metric Results (all patients)										108.6	92.6	0.00^
No. of Plans that Scored "0" (violated hard constraint (-150 pts)										0	8	

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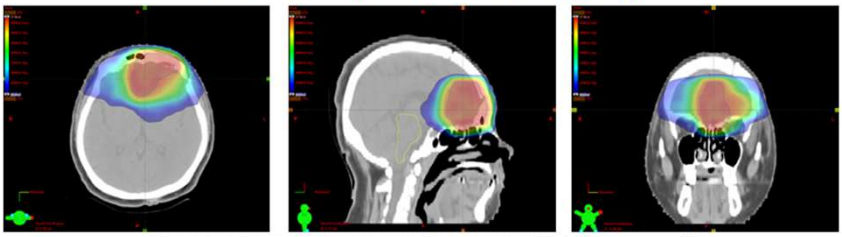
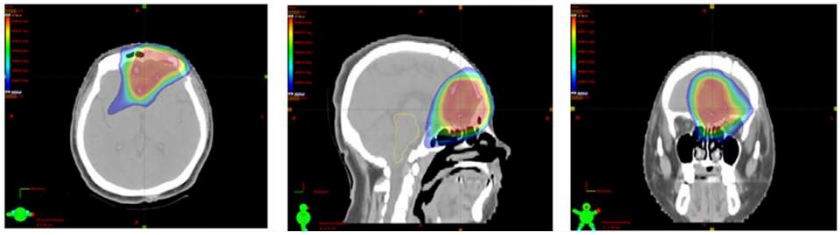
RTOG PLAN [102 POINTS (triangles)]

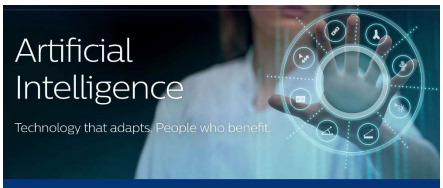


CLASS SOLUTION PLAN [123 POINTS (squares)]



Timely

Radonc Vendors – Artificial Intelligence



At Philips, we develop intelligent solutions that help healthcare providers achieve better outcomes, and that help [illegible] lifestyles. We do this by applying artificial intelligence in a meaningful way that improves people's lives.

Varian and Ping An Sign Memorandum of Understanding to Expand Access to High Quality Cancer Care in China

PRESS RELEASE PR Newswire
Jan. 8, 2018, 08:15 AM

SHARE

PALO ALTO, Calif. and BEIJING, Jan. 8, 2018 /PRNewswire/ -- Varian (NYSE: VAR) today announced it has signed a Memorandum of Understanding (MoU) with Ping An Health Technology Co., Ltd, to explore a strategic partnership for expanding access to cancer care in China. Leveraging their respective technical and domain expertise, the two companies will investigate the utilization of artificial intelligence, cloud computing and big data technologies, to deliver high quality and cost-effective cancer care to a far greater number of people in China, and close to where they live.

February 02, 2017

RAYSEARCH LICENSES AI TECHNOLOGY FOR AUTOMATED TREATMENT PLANNING FROM UHN

PDF

University Health Network (UHN) in Canada has exclusively licensed a new artificial intelligence (AI) technology for automated radiation therapy treatment planning to RaySearch, for incorporation into the RayStation® treatment planning system. The technology was developed by the Techna Institute, which is a collaboration between UHN and the University of Toronto.

The license gives RaySearch the ability to integrate deep-learning algorithms from Princess Margaret Cancer Centre's AI automated planning technology platform into RayStation. The technology will be built into RayStation's module for automated treatment planning across multiple treatment sites, enabling rapid adoption by clinical customers.

Elekta taps IBM Watson Health to bring AI to comprehensive oncology field

STOCKHOLM, January 31, 2018 – Elekta (EKTA-B.ST) today announced that it is collaborating with IBM Watson Health (https://www.ibm.com/watson/health/) to offer Watson for Oncology (https://www.ibm.com/watson/health/oncology-and-genomics/) with Elekta's cancer care solutions. Under the terms of a new agreement, Elekta will sell Watson for Oncology beginning in early 2018 as a clinical decision support solution paired within Elekta's digital cancer care solutions, including the MOSAIQ® Oncology Information System. Elekta intends to offer both solutions in most markets around the world including the U.S., Brazil, certain major European and Asian markets as well as India and Australia.

Timely

Non-Radonc Vendors Investing in AI

Imaging, Contouring & Treatment Planning

Microsoft

Project InnerEye – Medical Imaging AI to Empower Clinicians
Established: October 7, 2008

Google

DEEPMIND
DeepMind Health

IBM Watson

IBM Watson Health

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Timely

Non-Radonc Vendors Investing in AI

Artificial Intelligence + Clinical Decision Support

Oncora MEDICAL

Precision Radiation Oncology: *Predictive Analytics for Personalized Data-Driven Treatment Planning*

Calculate patient-specific toxicity risks	• Patient's overall risk of toxicities • Identifies a patient's overall risk of toxicities and provides breakdown of risk for many common radiation toxicities associated with the given diagnosis.
Design personalized radiation treatment plans	• Risk is determined by an advanced predictive model trained on past plans that combines the patient's attributes and medical history with the details of the current cancer diagnosis. • Several plans are generated based on past plans with similar characteristics.
Predict outcomes for proposed treatment plans	• Each plan has an assessment of toxicity and cure probabilities. • Final checks are made to ensure that the planned is predicted to have high cure probabilities and low toxicity probabilities.

Image Courtesy:

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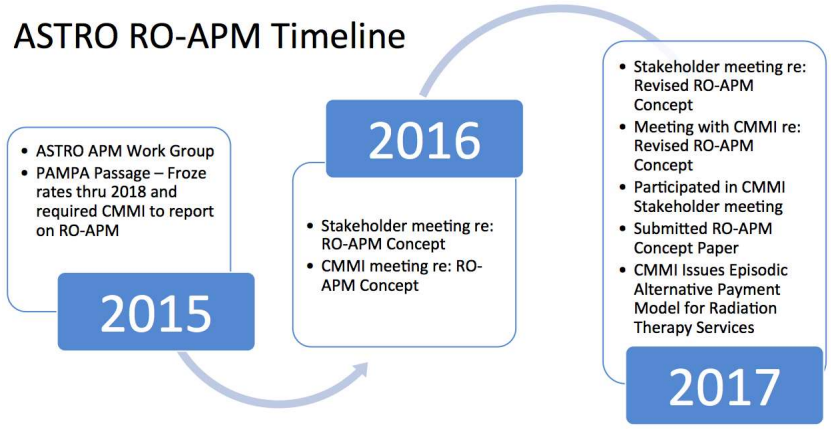
Radonc Value Based Models

1. PROMETHEUS Group & Roswell Park/Blue Cross
2. 21st Century Oncology (TDABC)
3. United Healthcare & MDACC
4. University of Texas System, MDACC & BCBS-TX
5. CMS/CMMI
6. ASTRO

ASTRO RO-APM

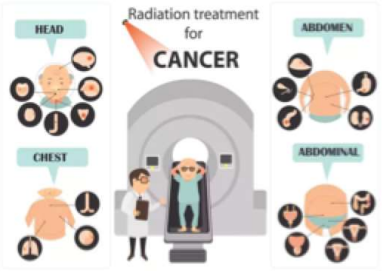


Courtesy: Anne Hubbard, ASTRO Director of Health Policy

ASTRO RO-APM

Guideline-Driven Radiation Oncology APM

- Guidelines adherence will improve quality and reduce unnecessary care and waste
  - ASTRO and NCCN guidelines, as well as Choosing Wisely guidance
- Standard APM payment framework applicable to all disease sites
- Applicable in Freestanding and Hospital Based Settings
- Quality Measures
  - MIPS Radiation Oncology Measures Set
  - APEx Accreditation or equivalent standards
  - Measures that determine compliance with guidelines
- Certified Electronic Health Records Technology



Courtesy: Anne Hubbard, ASTRO Director of Health Policy

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ASTRO RO-APM

ASTRO APM Payment Framework

Define Disease Group and Episode
- **Disease site**
- **Include all XRT services**
- **Establish standard regimen options**

Select reference period (2013-2015)

Apply adjustment for geographic & practice variation

Apply a 3% discount

Medicare's Target Price

Prospectively Paid to Radiation Oncologist at onset of Episode

Courtesy: Anne Hubbard, ASTRO Director of Health Policy

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ASTRO RO-APM

RO-APM – Key Components

- Designed to protect access to care and improve quality of care
- Stabilizes payment rates over a five year period
- Voluntary alternative to MIPS
- Provides Radiation Oncologists with an opportunity to actively participate in an APM
- Aligns with OCM
- Awards 5% Advanced APM participation bonus

Courtesy: Anne Hubbard, ASTRO Director of Health Policy

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APM Summary

1. APM should be as inclusive and operate as simple as possible
2. Build evidence-based/consensus-based clinical guidelines for all radiation oncology cases
3. Quality measures should emphasize process & outcomes
4. Payment schedule includes all common cancer diagnoses and services
5. Agreements with multi-year terms with annual payer-provider reviews

Constantine Mantz Chief Medical Officer 21st Century Oncology

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APM Summary

1. Utilization is assessed against contractual benchmarks (based on NCCN and other ASTRO guidelines) to evaluate for appropriate resource Utilization
2. Any new radiotherapy services are considered annually for inclusion
3. Physicians are in the best position develop APMs that will promote care quality and efficient resource utilization
4. **Operational Efficiencies - to reduce existing administrative and direct practice and improve revenue cycles times and payment predictability**

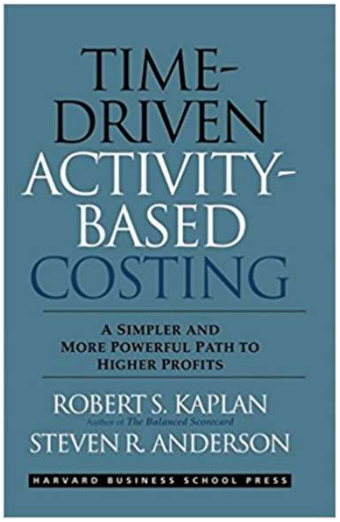
Efficient

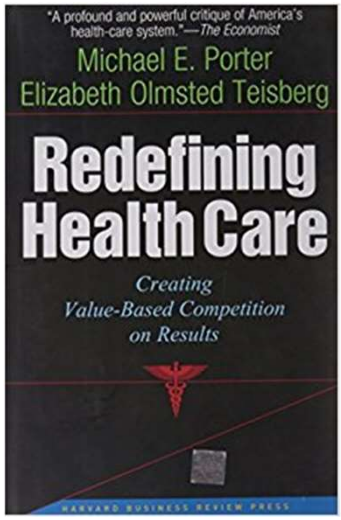
Importance of Operational Cost w/ APMs

1. How much does it cost to deliver 1 fraction?
2. Why? Defines Value to the provider/center, to the patient and to the healthcare system

Efficient

Time Driven Activity Based Costing





Efficient

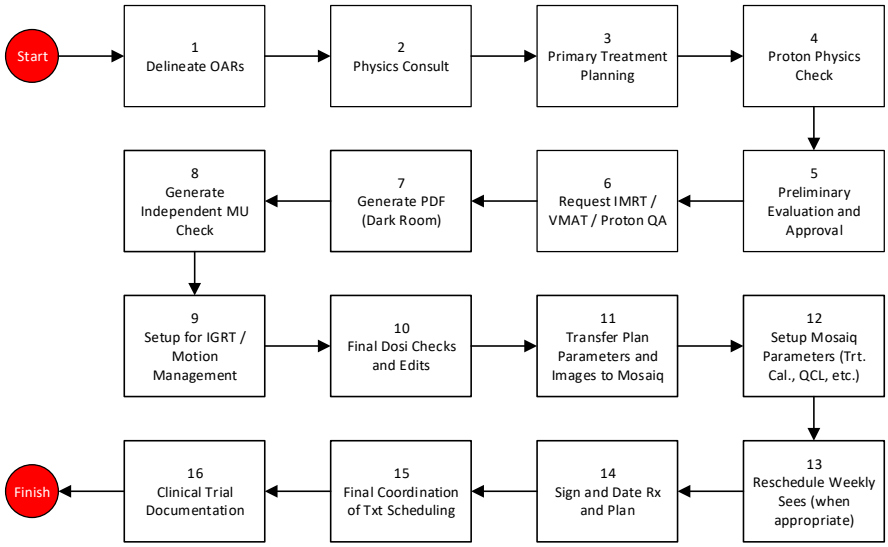
TDABC Project Strategy

- **Divide Division** — Decide how to split up the Division into pieces; (Clinical Service, Treatment Modality, Diagnosis, etc.)
- **Plan** — Detailed Project Plan with tasks and dates for each of the pieces
- **Pre work** — General Process Map for each piece
- **Edit Map** — Meet with multidisciplinary group of people who do the work and edit process map
- **Validate Map** — Validate the specific map with the corresponding team
- **Resources** — Assign Labor Resources to each task

Courtesy: Ben Frank, Provision & Nick Olivieri, MDACC

Efficient

TDABC Process Map Example



Courtesy: Ben Frank, Provision & Nick Olivieri, MDACC

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Efficient

TDABC Resources, Time, and Cost

Create Process Map → Calculate Resources → Enter Data Into Master File → Repeat for Each Process

Division of Radiation Oncology TDABC FY16/FY17 Ben Frank Nick Olivieri		Drop In All Modalities										
All times in minutes									Min weight 50%		Max weight 50%	
Process Step Number	Process Step	Step Frequency	Resources	Resource Frequency	Min Time	Max Time	Cost Rate per minute	Min Weighted Time	Max Weighted Time	Min Cost	Avg Cost	Max Cost
1	Patient Check In	100%	Receptionist	100%	2	4	$ 0.01	2.0	4.0	$ 0.02	$ 0.03	$ 0.04
		100%	PSC	100%	1	2	$ 0.01	1.0	2.0	$ 0.01	$ 0.02	$ 0.02
2	Vitals / Room	100%	RN	95%	4	8	$ 0.01	3.8	7.6	$ 0.04	$ 0.06	$ 0.08
		100%	MA	5%	4	8	$ 0.01	0.2	0.4	$ 0.00	$ 0.00	$ 0.00
3	RN Assessment	100%	RN	100%	10	20	$ 0.01	10.0	20.0	$ 0.10	$ 0.15	$ 0.20
4	APP / Resident	75%	APP	75%	10	15	$ 0.01	5.6	8.4	$ 0.06	$ 0.07	$ 0.08
		75%	RO Resident	25%	10	15	$ 0.01	1.9	2.8	$ 0.02	$ 0.02	$ 0.03
5	MD	25%	MD	100%	10	25	$ 0.01	2.5	6.3	$ 0.03	$ 0.04	$ 0.06
14	Verify Record of Tx Delivery	100%	LINAC	100%	0.5	1	100%	LINAC	100%	0.5	1	100%	LINAC	100%	0.5	1	100%	Proton Gantry	100%	1	1

Courtesy: Ben Frank, Provision & Nick Olivieri, MDACC

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Efficient

What if Scenarios

		3D/ 2D (Definitive)			IMRT/VMAT (Definitive)			Palliative			Proton		
	Number	Min Cost	Avg Cost	Max Cost	Min Cost	Avg Cost	Max Cost	Min Cost	Avg Cost	Max Cost	Min Cost	Avg Cost	Max Cost
Consult	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Sim	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Txt Plan Prep	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Planning Clinic	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Txt Planning	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Plan QA	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Txt Plan Corrections	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Txt Delivery	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Dry Run	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
I LD	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Pulse Check	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Weekly See	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Drop In	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Verification Sim	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Adaptive Txt Planning	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
EOT Workup	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Follow Up	0	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Total Cost		$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -

Modality	Min Cost	Avg Cost	Max Cost
3D/2D (Definitive)	$ -	$ -	$ -
IMRT / VMAT (Definitive)	$ -	$ -	$ -
Palliative	$ -	$ -	$ -
Proton	$ -	$ -	$ -

Courtesy: Ben Frank, Provision & Nick Olivieri, MDACC

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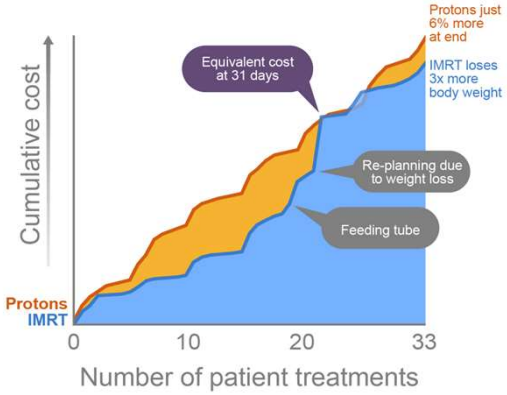
Efficient

TDABC Application

Comparative costs of advanced proton and photon radiation therapies: lessons from time-driven activity-based costing in head and neck cancer

Journal of Comparative Effectiveness Research

"Understanding provider costs will become even more important as healthcare reform transitions to value-based purchasing."



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The Value of a Dosimetrist

1. Healthcare is changing
2. Dosimetrists are central to radiation oncology
3. Dosimetrists role in safety, quality, and process improvement are key to value
4. Embrace change and contribute to the solutions
5. Demonstrate your value
6. Important to position the field now for the future

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Advancing the Dosimetry Profession

1. Perfect Position to be Radiation Oncology Physician Assistant
2. Clinical Education & Background Foundation
3. Technology and trends are changing in RO (SBRT/Hypofractionation, Imaging, Automation, AI)
4. Hospitals and Physicians want to reduce their administrative burden (contouring, image review, treatment planning, etc.) to focus on clinical care.
5. Insurance burden is increasing for all types of treatments

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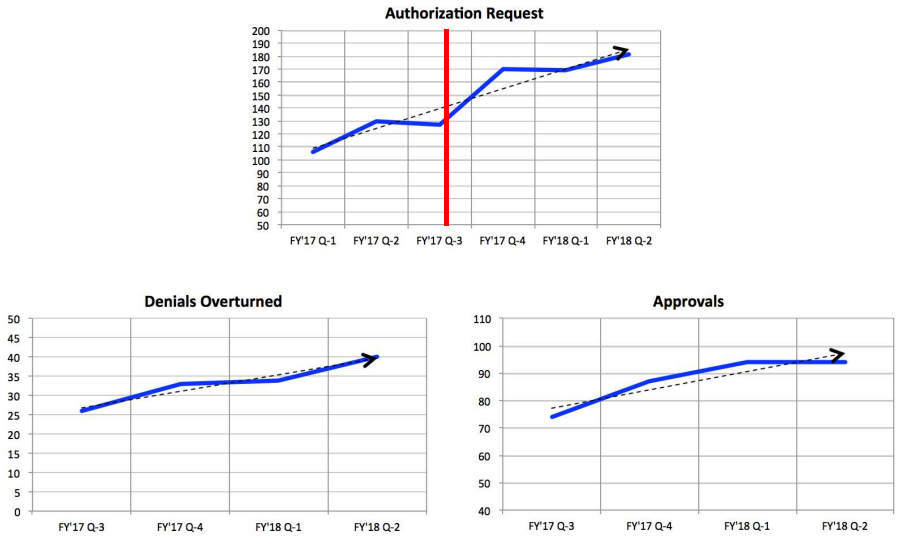
Clinic Program Manager

- Requires strong clinical oncology, dosimetry, and insurance (not necessary) background in order to be an advocate during the insurance authorization process.
- Management of the team during of the insurance authorization process from start to finish.
- The physicians' primary administrative point of contact.
- Work closely with the physician to develop a clinical strategy and advocacy for each patient.
- Perform or provide advice for Peer-to-Peers
- Involved in health policy initiatives with state commissioners and employer based plans.

Clinic Program Manager

- Receive Insurance 101 training
- Learning the keys for success for a hospital in a pay for value environment
- Additional responsibilities in development:
  - Attend new patient clinics
  - Assistance w/ physician documentation (draft consult note)
  - Comparative planning for insurance purposes

Clinic Program Manager Impact



Closing Remarks

1. Valuable clinical knowledge that can't be replaced
2. Key position in the radiation oncology workflow
3. Responsible for Outcomes
4. Innovators
5. Analytical
6. Focused on Safety and Quality

Conclusions

Dosimetrists have all the skills to be successful in a value based healthcare environment!

Participate in quality and new technology initiatives to show your value!

Support change, new technology, innovation, automation so you are part of the solution!

AAMD

Recommendation- Plan for the future now!

Develop Professional Growth and Educational Models for a future Advanced Practice Dosimetrist role.

Questions?

Contact Information:

mpalmer@mdanderson.org