Application and Potential of Model-Based Planning in Proton Therapy

Anthony Mascia, PhD
Director of Medical Physics
Cincinnati Children's Hospital
University of Cincinnati
anthony.mascia@cchmc.org

Disclosures

The Department of Radiation Oncology at Cincinnati Children's Hospital and University of Cincinnati has a research agreement with Varian Medical Systems.

Last presentation. Last session. Last day

"We wanted to save the best for last."
- Katja Langen

"You must think I was born yesterday."
- Anthony Mascia

Outline

- Treatment planning
- Model-based treatment planning
  - Applications and utility
  - Results
- Future work

Treatment Planning

Current Practices

Unique Factors in Proton Treatment Planning

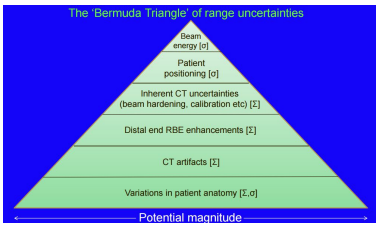
"Find out *exactly* how many ways there are to skin a cat."

- Beam angle selection
- LET evaluation / optimization
- Emerging and evolving delivery modalities
  - Proton arc therapy, FLASH therapy, GRID therapy, PBS + MLC, etc.
- Range uncertainty
- Nozzle and beam modifiers (e.g. range shifters, collimators, apertures, etc)
- PTV optimization
- Robust evaluation / optimization
- And so forth…

Unique Factors in Proton Treatment Planning

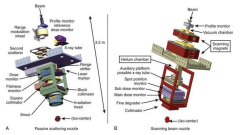
- Beam angle selection
- LET evaluation / optimization
- New emerging or potential technologies, like proton arc therapy, FLASH therapy, GRID therapy, PBS+MLC, etc

Range Uncertainty

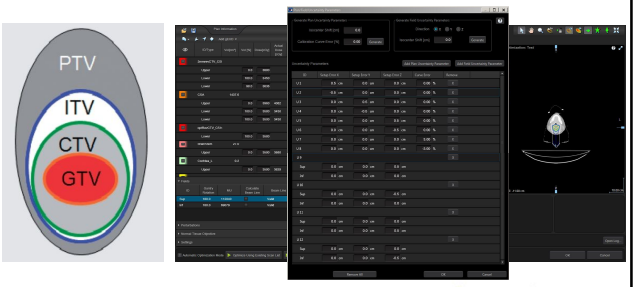


Antony Lomax. AAPM Summer School 2013

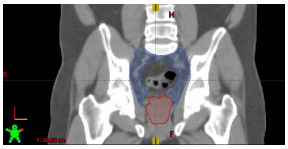
Gantry, Nozzle and Beam Modifiers



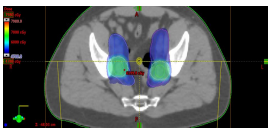
Robust Optimization

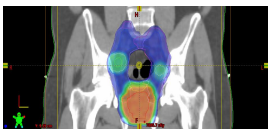


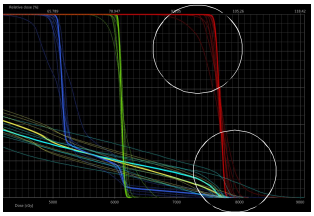
Example: Prostate + Nodes



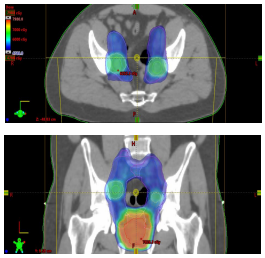
Optimizations: PTV vs. Robust

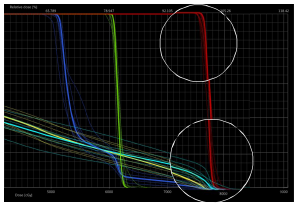




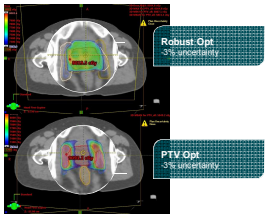


Optimizations: PTV vs. Robust

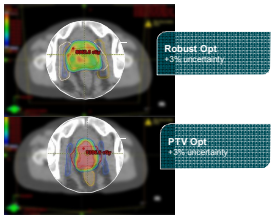




Range Uncertainty Mitigation RO vs. PTV



Range Uncertainty Mitigation RO vs. PTV



AI in Radiation Oncology

AI in Radiation Oncology

Contents lists available at ScienceDirect

Radiotherapy and Oncology

journal homepage: www.thegreenjournal.com

Review

Artificial intelligence in radiation oncology: A specialty-wide disruptive transformation?

Reid F. Thompson [a,b,*], Gilmer Valdes [c], Clifton D. Fuller [d], Colin M. Carpenter [e], Olivier Morin [c], Sanjay Aneja [f], William D. Lindsay [g], Hugo J.W.L. Aerts [h,i], Barbara Agrimson [a], Curtiland Deville Jr. [j], Seth A. Rosenthal [k], James B. Yu [l], Charles R. Thomas Jr [a]

[a] Oregon Health & Science University, Portland; [b] VA Portland Health Care System, Portland; [c] University of California San Francisco; [d] MD Anderson Cancer Center, Houston; [e] Sirio Medical, Inc, Redwood City; [f] Yale University, New Haven; [g] Onconx Medical, Philadelphia; [h] Brigham and Women's Hospital, Boston; [i] Dana Farber Cancer Institute, Boston; [j] Johns Hopkins University School of Medicine, Baltimore; and [k] Sutter Medical Group and Sutter Cancer Center, Sacramento, USA

AI in Radiation Oncology

- Image segmentation
- Dose optimization
- Clinical decision support and outcome prediction
  - Pre-planning outcome predictions
  - Cross-correlating radiation oncology with genomics, imaging, EMRs
  - Quantitative imaging
- Quality assurance

Some comments and limitations

- Generally, Radiation Oncology datasets have been small relative to other professions
- Lack of access to high quality, standardized therapy and outcome data is an obstacle
- Specifically, on planning, knowledge-based planning has shown to:
  - Increase efficiency
  - Improve standardization
  - Provide a quality assurance tool\
  - **"The need is emerging for QA of AI-based processed and other clinically deployed algorithms"**

Knowledge-based planning

Knowledge-based planning aspects

- Dosimetric predictions
- Patient selection
- Clinical decision support
- Quality assurance
- Improved plan quality and efficiency
- Knowledge sharing

Predicting potential dosimetric benefits

International Journal of Radiation Oncology Biology • Physics
www.redjournal.org

Physics Contribution

Predicting Patient-specific Dosimetric Benefits of Proton Therapy for Skull-base Tumors Using a Geometric Knowledge-based Method

David C. Hall, DPhil, Alexei V. Trofimov, PhD, Brian A. Winey, PhD, Norbert J. Liebsch, MD, PhD, and Harald Paganetti, PhD

Department of Radiation Oncology, Massachusetts General Hospital and Harvard Medical School, Boston, Massachusetts

Received Sep 9, 2016

- Using at least 20 patients, models for several OARs are created and validated against at least 20 other patients
- Model used to predict proton benefits for photon patients

Model Prediction Correlated to Actual Planned Dose Distributions

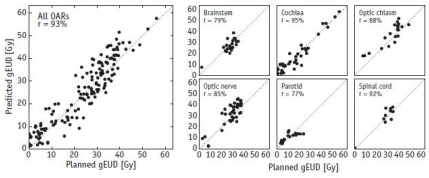


Fig. 4. Predicted generalized equivalent uniform dose (gEUD) versus planned gEUD for every organ at risk structure in the validation cohort (Left) and a breakdown by organ at risk type (Right). Pearson's *r* also shown.

Patient selection using knowledge base

Radiotherapy and Oncology 124 (2017) 263–270
Contents lists available at ScienceDirect
Radiotherapy and Oncology
journal homepage: www.thegreenjournal.com

Knowledge-based selection

Using a knowledge-based planning solution to select patients for proton therapy

Alexander R. Delaney *, Max Dahele, Jim P. Tol, Ingrid T. Kuijper, Ben J. Slotman, Wilko F.A.R. Verbakel

Department of Radiation Oncology, VU University Medical Center, Amsterdam, The Netherlands

- Patient selection is high priority in proton therapy, particularly in regional or national healthcare systems
- Model created for photon and proton for H&N patients

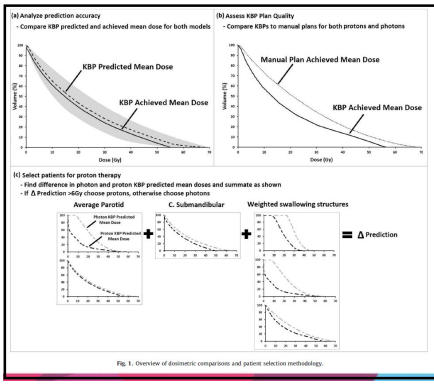
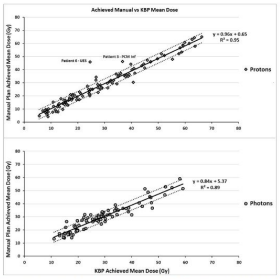


Fig. 1. Overview of dosimetric comparisons and patient selection methodology.

Methodology

- Compare predicted and actual plans
- Validate plan quality
- Devise a selection criteria for sorting patients potentially for photon and proton

Manual Doses and KBP Prediction Doses Correlate



- For photon, KBP OAR dose often better than manual (slope = 0.84)
- For proton, KBP OAR dose nearer to manual (slope = 0.96)
- NTCP models may be tied to such predictions, if desired

Step further in clinical decision support…


Radiotherapy and Oncology

Decision support system

Clinical decision support of radiotherapy treatment planning: A data-driven machine learning strategy for patient-specific dosimetric decision making

- Using plan classification and course feature definitions, a clinical decision support model constructed
- Model for H&N proton found at least 30 patients are needed for model
- Provide information prior to planning

Clinical Decision Support

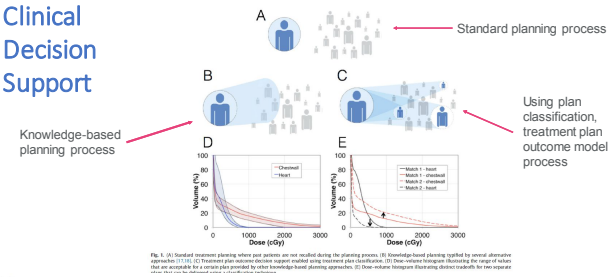


Fig. 1. (A) Standard treatment planning where past patients are not recalled during the planning process. (B) Knowledge-based planning typified by several alternative approaches [17,18]. (C) Treatment plan outcome decision support enabled using treatment plan classification. (D) Dose–volume histogram illustrating the range of values that are acceptable for a certain plan provided by other knowledge-based planning approaches. (E) Dose–volume histogram illustrating distinct tradeoffs for two separate

Table 1
Feature-set categories used to predict dose for a radiation treatment plan.

Feature category	Example features
Anatomical information	Distance, volume, geometric relationship, and importance of structures and surrounding structures
Medical record	ICD-9/10 code, gender, ethnicity
Treatment intent	Fractionation schedule, treatment margin, number of beams/arcs, and the clinicians who are part of the team creating the radiation treatment plan
Radiation transport	Penumbra, aperture, incident angle, beam energy, radiation type (proton vs photon), depth of structure, and existence of bolus

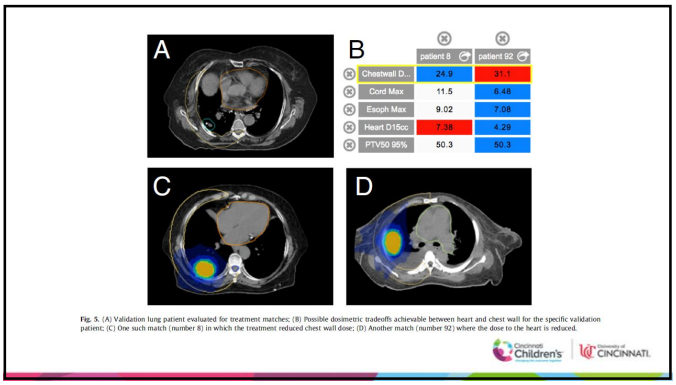


Fig. 5. (A) Validation lung patient evaluated for treatment matches; (B) Possible dosimetric tradeoffs achievable between heart and chest wall for the specific validation patient; (C) One such match (number 8) in which the treatment reduced chest wall dose; (D) Another match (number 92) where the dose to the heart is reduced.

Quality assurance

Practical Radiation Oncology (2019) 9, e218–e227

Basic Original Report

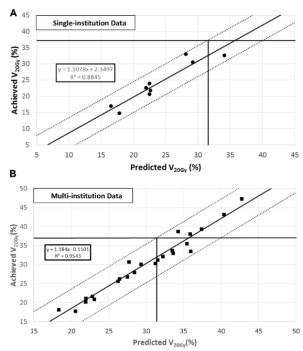
Multi-Institutional Validation of a Knowledge-Based Planning Model for Patients Enrolled in RTOG 0617: Implications for Plan Quality Controls in Cooperative Group Trials

James A. Kavanaugh MS [a,*], Sarah Holler BS [b], Todd A. DeWees PhD [c], Clifford G. Robinson MD [d], Jeffrey D. Bradley MD [d], Puneeth Iyengar MD, PhD [d], Kristin A. Higgins MD [e], Sasa Mutic PhD [f], Lindsey A. Olsen PhD [f]

[a]Department of Radiation Oncology, Washington University in St Louis, St Louis, Missouri; [b]Department of Radiation Oncology, Virginia Commonwealth University, Richmond, Virginia; [c]Division of Biomedical Statistics and Informatics, Mayo Clinic, Scottsdale, Arizona; [d]Department of Radiation Oncology, University of Texas Southwestern, Dallas, Texas; [e]Department of Radiation Oncology, Emory University, Atlanta, Georgia; and [f]University of Colorado Health System, Colorado Springs, Colorado

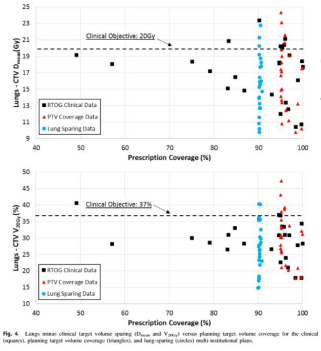
Received 16 April 2018; accepted 19 November 2018

- Using institutional models to quality assurance patient on clinical trial
- Institutional model used to identify potential outliers, then also model possible improvements given a different optimization approach



Identifying cases for review

- Using a single institution's model:
  - Patients on trial with outliers, in this case V20 > 37%, can be identified for review or additional planning optimization

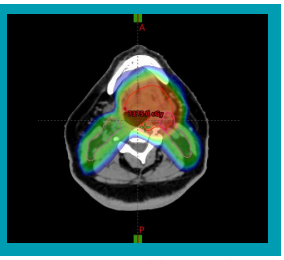


Potential to improve plan quality on clinical trial setting

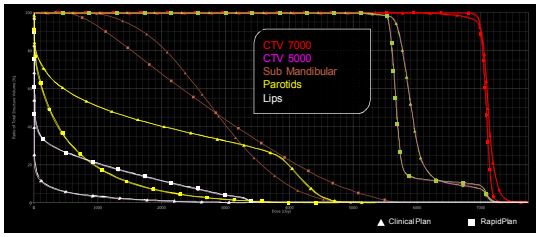
- On trial, based on this study, institutions often sacrificed coverage for OAR dose
- By using model, in many cases, these trade-off can be rebalanced

University of Cincinnati Initial Collaboration on KBP

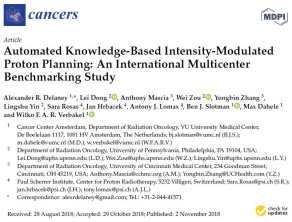
Cincinnati Children's began pilot project with Varian and VUMC testing a RapidPlan model using our patient datasets



Initial Collaboration and Experience with VUMC



Improved efficiency, quality and sharing



cancers

MDPI

Article

Automated Knowledge-Based Intensity-Modulated Proton Planning: An International Multicenter Benchmarking Study

Alexander R. Delaney [1,*], Lei Dong [2], Anthony Mascia [3], Wei Zou [2], Yongbin Zhang [3], Lingchu Yin [2], Sara Rosas [4], Jan Hrbacek [4], Antony J. Lomax [4], Ben J. Slotman [1], Max Dahele [1] and Wilko F. A. R. Verbakel [1]

1 Cancer Center Amsterdam, Department of Radiation Oncology, VU University Medical Center, De Boelelaan 1117, 1081 HV Amsterdam, The Netherlands; bj.slotman@vumc.nl (B.J.S.); m.dahele@vumc.nl (M.D.); w.verbakel@vumc.nl (W.F.A.R.V.)
2 Department of Radiation Oncology, University of Pennsylvania, Philadelphia, PA 19104, USA; Lei.Dong@uphs.upenn.edu (L.D.); Wei.Zou@uphs.upenn.edu (W.Z.); Lingchu.Yin@uphs.upenn.edu (L.Y.)
3 Department of Radiation Oncology, University of Cincinnati Medical Center, 234 Goodman Street, Cincinnati, OH 45219, USA; Anthony.Mascia@uchmc.org (A.M.); Yongbin.Zhang@UCHealth.com (Y.Z.)
4 Paul Scherrer Institute, Center for Proton Radiotherapy, 5232 Villigen, Switzerland; Sara.Rosas@psi.ch (S.R.); jan.hrbacek@psi.ch (J.H.); tony.lomax@psi.ch (A.J.L.)
* Correspondence: alexrdelaney@gmail.com; Tel.: +31-2-044-41371

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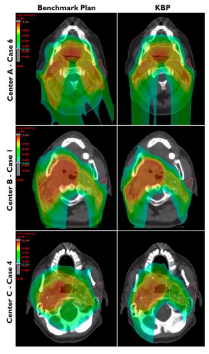
check for updates

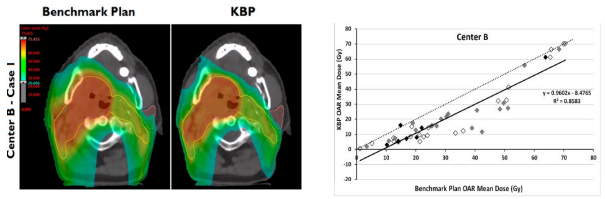
- Multi-institutional study
  - VUMC
  - UPenn
  - PSI
  - University of Cincinnati
- Clinical ("benchmark") plans vs. Knowledge-based plans (KBP)



General Observations

- KBP had at least same CTV coverage at Benchmark
- KBP achieved similar (or better) normal tissue sparring
- Beam angle selection in the model vs. clinic matters
- Knowledge-based model, if well curated, produced at least clinically acceptable (and in many cases improved) results
- KBP may improve efficiency (e.g. KBP optimization was approx. 8 min)… however more thorough study on this is warranted

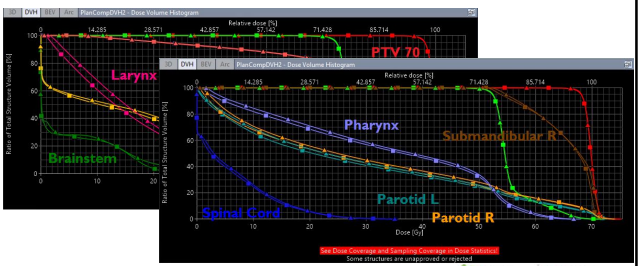
KBP vs. Clinical Plans



Some practical gaps in applying KBP

- Release of technology
- Enhance knowledge sharing
  - Particularly important in emerging technologies and/or in regions with limited experienced staff
- Generalization of models
  - Beam angle optimization or selection
  - PTV and robust optimization
  - Inter-facility differences in hardware and procedure (i.e. range shifters, range uncertainty quantification and management, etc)
- Incorporating additional patient information
  - For example, radiosensitivity, risk tolerances, re-irradiation setting, etc.

Knowledge Sharing – VUMC & Cincinnati



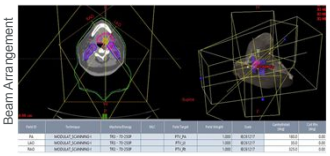
Courtesy Alex Delaney, VUMC & Yongbin Zhang, Children's/UC

Moving Forward: University of Cincinnati H&N Model

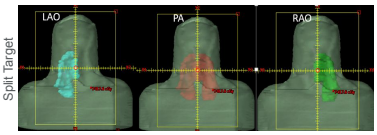
- Build using clinical patients (H&N, oropharynx)
- Test model against clinical plans
- Assess model generalization for robust optimization
- Presented at AAPM 2018:
  - Yongbin Zhang, et al. "Toward Statistical Model-Based Robust IMPT Planning: Cross-Validation and Robust Generalization", AAPM 2018
  - *Manuscript in process*

Build model

Beam Arrangement



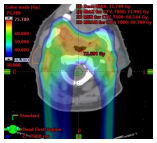
Split Target



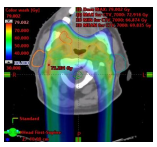
PTV Expansion

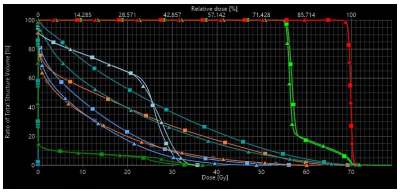
Case by Case Comparisons: Clinically Acceptable?

Clinical



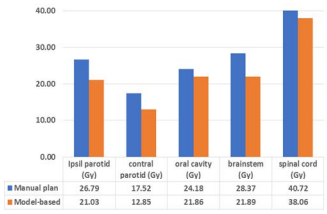
Model





Yongbin Zhang, et al. "Toward Statistical Model-Based Robust IMPT Planning: Cross-Validation and Robust Generalization", AAPM 2018

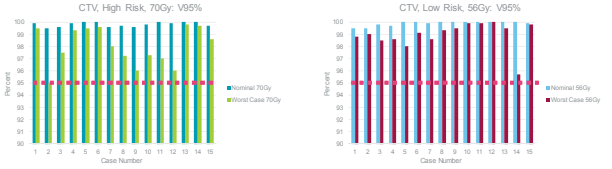
Case by Case Comparisons: Clinical Acceptable?



	Ipsil parotid (Gy)	contral parotid (Gy)	oral cavity (Gy)	brainstem (Gy)	spinal cord (Gy)
Manual plan	26.79	17.52	24.18	28.37	40.72
Model-based	21.03	12.85	21.86	21.89	38.06

Yongbin Zhang, et al. "Toward Statistical Model-Based Robust IMPT Planning: Cross-Validation and Robust Generalization", AAPM 2018

Nominal & Worst-Case Robustness Coverage?

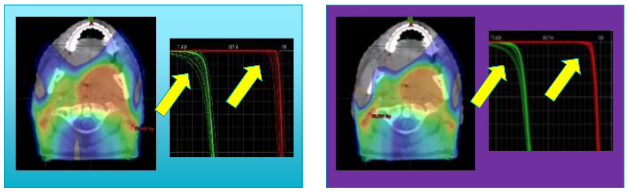


Yongbin Zhang, et al. "Toward Statistical Model-Based Robust IMPT Planning: Cross-Validation and Robust Generalization", AAPM 2018

Model Apply to Robustness Optimization?

Manual / Clinical Plans

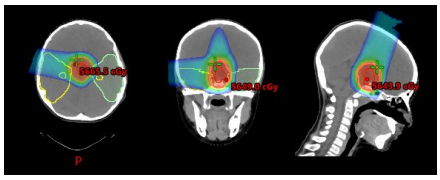
Model-based Plans



Yongbin Zhang, et al. "Toward Statistical Model-Based Robust IMPT Planning: Cross-Validation and Robust Generalization", AAPM 2018

Additional Clinical RapidPlan Evaluation at CCHMC

Craniopharyngioma



Axial Coronal Sagittal

Anthony Mascia, et al. "Toward Class Solution for Craniopharyngioma", PTCOG 2017

Summary

- Proton planning has unique aspects (eg, range uncertainty, beam angle selection, PTV and robust optimization methods, etc) presenting challenges to model creation
- Knowledge-based models require more patient data (ie, some studies showing 30 or more for a single model with a single purpose)
- Knowledge-based planning models may
  - Predict dosimetric advantages
  - Improve efficiency
  - Improve standardization
  - Provide quality assurance
  - Pair with clinical decision support models
- Knowledge-based planning is part of the AI future in Radiation Oncology

Acknowledgements

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Dana Blasongame, CMD
Sarah Johnson, CMD
Joseph Speth, BS
Anthony Mascia, PhD

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John Breneman, MD
Luke Pater, MD
Ralph Vatner, MD, PhD
Kevin Redmond, MD
Jordan Kharofa, MD
Teresa Meier, MD

Multi-institutional Collaborators
Wilko Verbakel, PhD (VUMC)
Alex Delaney, PhD (VUMC)
Tony Lomax, PhD (PSI)
Lei Dong, PhD (UPenn)

Vendor Collaborators
Christel Smith, PhD
Reynald Vanderstraeten

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