planning and 3-month-followup CT scans. Hypertrophy was binarized by thresholding volumetric increase>7.6cc and 8.5cc for left and right liver. In cohort-1,120 clinical/dosimetric features of patients were filtered using Chi-squared/Fisher-Exact test and Logistic regression. Hypertrophy prediction models for right and left liver were trained using Lasso regression, support vector machine, random forest, XGBoost, Gaussian Process, and Naïve Bayes with train/test split of 148/37 with 10-fold cross validation. Models were assessed via AUROC, sensitivity/specificity, and accuracy. Majority voting (MV) was applied on all models to determine final predictions. In cohort-2, an in-house AI model was used to construct IMRT doses on 20 independent patients who originally received 3DCRT photon treatments. Dosimetric features from both RT groups were separately input to the best hypertrophy prediction models obtained from cohort-1.

Results: Mean Hounsfield Unit (as a surrogate for steatosis) and right liver volume spared from $25Gy_{EQD2}$ were significant($p<0.05$) predictors of right liver hypertrophy. Tumor location, minimum dose to 95% of GTV, mean doses to right and left liver volume spared from $40Gy_{EQD2}$ were significant predictors of left liver hypertrophy($p<0.05$). In cohort-1, XGBoost showed the best scores with AUROC, sensitivity, specificity, and accuracy of 0.72, 0.79, 0.65, 0.68 for right liver. For left liver, MV showed best AUROC, sensitivity, specificity, and accuracy of 0.65, 0.79, 0.50, 0.65, respectively. In cohort-2, for right liver hypertrophy, 3/20 patients showed hypertrophy with both RT plans, 2/20 showed hypertrophy for only 3D, and 2/20 showed hypertrophy for only IMRT. For left liver hypertrophy, 5/20 patients showed hypertrophy using IMRT only, but no patients showed hypertrophy using 3D-plan only. 13/20 patients showed hypertrophy using both plans.

Conclusion: Tumor location and liver volume spared from specific RT doses are significant predictors of hypertrophy. ML can describe the liver hypertrophy with reasonable accuracy. Liver hypertrophy varies with dose distribution, which signals RT plans can be optimized to maximize liver hypertrophy.

Author Disclosure: **A.C. Gupta**: None. **M. Al Taie**: None. **I. Vazquez**: None. **A. Castelo**: None. **D.B. Flint**: None. **T.T. Tang**: None. **A.S. Prasad**: None. **Y. Zha**: None. **S. Robles**: None. **C. O'Connor**: None. **A.O. Leone**: None. **L.E. Court**: None. **M. Yang**: None. **S. Yedururi**: None. **J. Wu**: None. **J.P. Long**: None. **R.M. Howell**: elected (and voting) member of the AAPM Board of Directors; American Association of Physicists in Medicine. **E.J. Koay**: None. **K.K. Brock**: Grant/research funding; RaySearch Laboratories. Copyright/Patent/License/Royalty; RaySearch Laboratories.

1145

Institution Volumetric Modulated Arc Therapy Total Body Irradiation Technique Using Autoplanning Scripts: 4 Year Experience

N. Kovalchuk,[1] E.A. Simiele,[2] C. Hui,[3] L. Skinner,[3] Y. Yang,[1] M.S. Binkley,[3] R.T. Hoppe,[3] and S.M. Hiniker[3]; *[1]Department of Radiation Oncology, Stanford University, Stanford, CA, [2]University of Alabama Birmingham School of Medicine, Birmingham, AL, United States, [3]Department of Radiation Oncology, Stanford University School of Medicine, Stanford, CA*

Purpose/Objective(s): To report on the 4-year experience with implementation of the VMAT TBI autoplanning scripts at our institution. The scripts were made publicly available and have been recently included on the COG ASCT2031 trial.

Materials/Methods: Hundred patients underwent VMAT TBI treatment at our institution from October 2019 to October 2023. Treatment planning utilized a treatment planning tool's autoplanning scripts for 90 out of 100 patients. Data on dosimetric indices, treatment characteristics, robustness of performing local and global isocenter shifts of 5 mm, and in-vivo measurements on the matchline was collected and analyzed.

Results: For all 100 patients the lungs, lungs-1cm, and kidneys D_{mean} were consistently spared to 59.8±4.6%, 43.1±6.4%, and 70.7±7.5% of the prescription dose, respectively. Gonadal sparing (D_{mean}=31.1±6.0%) was achieved for all patients with benign disease. The average PTV D_{1cc} was 120.3±6.4% for all patients. PTV D_{1cc} correlated with patient height and width (R^2 = 0.62 and 0.53). Seventeen patients (17%) with height <116cm were treated with 3-isocenter VMAT only plans, 83 patients (83%) were treated with 3-4 isocenter VMAT plans in head-first-supine (HFS) position and 1-3 AP/PA plan in feet-first-supine (FFS) position. Custom-made rotational platform was used to change the patient orientation from HFS to FFS. For the first 10 patients, robustness evaluation showed that the PTV D_{max} and lungs D_{mean} are insensitive to small positioning deviations between the VMAT isocenters (1.1±2.4% and 1.2±1.0%, respectively). The average matchline dose measurement indicated patient setup was reproducible (96.1±4.5% relative to planned dose). For the first 35 patients, treatment time, including patient setup and beam-on, was 47.5±9.5 min.

Conclusion: VMAT TBI offers advantages over conventional 2D TBI, including organ sparing and dose painting, accurate dose calculation and image-guided delivery. The automated scripts enable streamline planning (approximately 4-5 hours) with consistent plan quality.

Author Disclosure: **N. Kovalchuk**: None. **E.A. Simiele**: None. **C. Hui**: None. **L. Skinner**: None. **Y. Yang**: None. **M.S. Binkley**: None. **R.T. Hoppe**: None. **S.M. Hiniker**: None.

1146

Deep Learning-Based Dose Prediction for Thoracic Radiation in a Statewide Radiation Oncology Quality Consortium

D. Polan,[1] C. Hadley,[1] C. Matrosic,[1] M. Grubb,[1] S. Jolly,[1] P.A. Paximadis,[2] and M.M. Matuszak[1]; *[1]Department of Radiation Oncology, University of Michigan, Ann Arbor, MI, [2]Department of Radiation Oncology, Corewell Health South, St. Joseph, MI*

Purpose/Objective(s): Knowledge-based planning (KBP) has been demonstrated to be a valuable tool for consistently guiding radiation therapy (RT) plan optimization and accessing plan quality. However, vendor specific implementations make it challenging to distribute necessary KBP components, such as dose prediction models, for multi-institutional use. Therefore, implementation of vendor-neutral, open-source KBP frameworks may assist in reducing distribution barriers and ensuring equal access to quality assurance and improvement tools. This work evaluates the performance of independent deep learning (DL)-based dose prediction models for use in a distributable KBP framework to support thoracic RT quality improvement in a statewide radiation oncology quality consortium.

Materials/Methods: 202 conventionally fractionated lung cancer RT plans clinically delivered between 2022 and 2023 were collected from 22 institutions with a variety of commercial treatment planning systems. All plans were optimized for 60 Gy in 30 fractions and met consortium guidelines for contour and dosimetric quality. Data were divided into 162 training cases and 40 validation cases, retaining at least one case from each institution for the training group. Two open-source DL architectures, a hierarchically densely connected U-net (HD U-net) and Cascading U-net (C3D), were evaluated based on prior demonstrated performance for head-and-neck cancer dose prediction. Performance of the models was evaluated using voxel and DVH-based mean absolute error (MAE) and 13 specific DVH metrics of interest for lung-directed RT.

Results: Based on MAE, the C3D architecture outperformed the HD U-net with voxel and DVH scores of 1.8 ± 1.2 (3.0 ± 2.0% of prescription dose) and 1.4 ± 0.6, compared to 2.4 ± 1.4 (4.0 ± 2.3%) and 1.4 ± 0.5. For DVH metrics, the C3D model provided significantly (paired T-test, $p < 0.05$) better performance for Heart $D_{0.03cc}$, Lungs-GTV/IGTV V_{5Gy}, and PTV $_{D0.1cc}$, whereas the HD U-net only demonstrated better performance for Lungs-GTV/IGTV V_{20Gy}. For the remaining 9 DVH metrics, differences were not statistically significant. For both models, the largest average prediction errors were found for DVH metrics representing near maximum dose (e.g., spinal cord $D_{0.1cc}$). Between the models, prediction error for all evaluated metrics was moderately or significantly correlated (Spearman rank order) except for target $D_{95\%}$.

Conclusion: The evaluated prediction models provide comparable accuracy to previously reported studies despite application in a unique multi-institutional dataset with diverse planning methods. Although the C3D model outperformed the HD U-net, correlations suggest that performance is more dependent on the case than architecture. Implementation of the models will assist in providing an equally accessible dose prediction model to enable statewide RT quality improvement.

Author Disclosure: **D. Polan**: Co-Director of Conference; Winter Insitute of Medical Physics. **C. Hadley**: None. **C. Matrosic**: None. **M. Grubb**: salary support for MROQC; Blue Cross Blue Shield of Michigan. **S. Jolly**: salary support for MROQC; Blue Cross Blue Shield of Michigan. Salary support; AstraZeneca, Varian Medical Systems. **P.A. Paximadis**: None. **M. M. Matuszak**: Grant/research funding; Varian. Licensing and Collaboration Agreement; Fuse Oncology. Board Member at Large; AAPM.

1147

Clinical Implementation of an Automated VMAT Treatment Planning Script for Head and Neck Cancer Patients: 3 Year-Experience

N. Kovalchuk,[1] P. Dong,[2] M. Xiang,[3] E.J. Moding,[4] M.F. Gensheimer,[5] B.M. Beadle,[5] Q.T. Le,[6] L. Xing,[1] and Y. Yang[1]; *[1]Department of Radiation Oncology, Stanford University, Stanford, CA, [2]Stanford University School of Medicine, Stanford, CA, [3]Department of Radiation Oncology, University of California, Los Angeles, Los Angeles, CA, [4]Department of Radiation Oncology, Stanford University School of Medicine, Stanford, CA, [5]Radiation Oncology, Stanford University, Stanford, CA, [6]Stanford University, Stanford, CA*

Purpose/Objective(s): This study aimed to assess the impact of implementing an in-house automated VMAT treatment planning script for patients with head and neck (HN) cancer.

Materials/Methods: The automated planning script, developed using a treatment planning tool, was introduced in 2020 for HN cancer patients. To evaluate its efficacy, dosimetric indices for 1000 patients treated between 2017 and 2023 were compared, with 500 patients planned manually and 500 patients planned using the automated script. Differences in target and organ-at-risk metrics were analyzed using a t-test, with $p < 0.05$ considered significant. Additionally, 5 radiation oncologists blindly reviewed 20 plans (10 auto- and 10 manual) and assessed their clinical acceptability and preference for treatment.

Results: Compared to the manually generated clinical head and neck plans, all auto plans achieved PTV $D_{95\%}$ coverage and critical organs at risk sparing without statistically significant change in average global D_{max} (107.4% for manual vs 107.5% for automated plans). The auto-planning solution provided reduced maximum doses to brainstem and spinal cord (average reductions of 3.6 ± 0.1 Gy and 2.1 ± 1.1 Gy, respectively, all $p < 0.001$), reduced average mean doses to contralateral submandibular gland, ipsilateral parotid, oral cavity, cochleae, larynx, contralateral parotid (reductions of 4.1 ± 1.2 Gy, 3.9 ± 0.4 Gy, 2.5 ± 0.1 Gy, 2.4 ± 0.2 Gy, 2.0 ± 1.4 Gy, 1.5 ± 0.1 Gy, respectively, all $p < 0.03$) and reduced average maximum doses to mandible and lips (reductions of 2.9 ± 2.8 Gy and 2.3 ± 1.2 Gy, respectively, all $p < 0.04$). In the blinded review by physicians, out of 50 responses 94% considered auto-plans clinically acceptable versus 86% for manual plans. Overall, 7 auto-plans were preferred for treatment, 1 was deemed equivalent, while only 2 manual plans were preferred.

Conclusion: The automated treatment planning script significantly improved plan quality for HN cancer patients by reducing important dosimetric indices to organs at risk while maintaining target coverage and dose homogeneity. Radiation oncologists appreciate reproducibility and efficiency of the auto-planning script in generating high-quality plans within a short timeframe.

Author Disclosure: **N. Kovalchuk**: None. **P. Dong**: None. **M. Xiang**: None. **E.J. Moding**: Compensation/Payment; Gerson Lehrman Group, Guidepoint. **M.F. Gensheimer**: None. **B.M. Beadle**: Royalties; Wolters-Kluwer, Elsevier. **Q. Le**: Honoraria; Nanobiotix, Coherus. Travel expenses; Coherus, Roche/Genentech. Leading RTOGF group for clinical trials; NRG Oncology/ RTOGF. **L. Xing**: None. **Y. Yang**: None.

1148

General and Organ Specific Consensus Recommendations for Stereotactic Body Radiotherapy Dose Prescription according to ICRU Report 91 from Working Groups on Stereotactic Radiotherapy

T.B. Brunner,[1] J. Boda-Heggemann,[2] D. Buergy,[2] S. Corradini,[3] U.K. Dieckmann,[4] S. Gerum,[5] E. Gkika,[6] J. Hoerner-Rieber,[7] S. Kirste,[8] R. Klement,[9] C. Moustakis,[10] M. Niyazi,[11] A. Ruehle,[10] S. Tanadini-Lang,[12] P. Winkler,[13] B. Zurl,[14] and O. Blanck[15]; *[1]Medical University of Graz, Dept. of Radiation Oncology, Graz, Austria, [2]Department of Radiation Oncology, University Medicine Mannheim, Medical Faculty Mannheim, Heidelberg University, Mannheim, Germany, [3]Department of Radiation Oncology, University Hospital, LMU Munich, Munich, Germany, [4]Department of Radiation Oncology, Medical University of Graz, Graz, Austria, [5]Department of Radiotherapy and Radiation Oncology, Paracelsus Medical University, Landeskrankenhaus, Salzburg, Austria, [6]Department of Radiation Oncology, University Hospital Bonn, Bonn, Germany, [7]Department of Radiation Oncology, University Hospital Heidelberg, Heidelberg, Germany, [8]German Cancer Consortium (DKTK), Partner Site Freiburg, Heidelberg, Germany, [9]Department of Radiotherapy and Radiation Oncology, Leopoldina Hospital Schweinfurt, Schweinfurt, Germany, [10]Department of Radiation Oncology, University Hospital Leipzig, Leipzig, Germany, [11]Department of Radiation Oncology, University Hospital Tübingen, University of Tübingen, Tübingen, Germany, [12]Department of Radiation Oncology, University Hospital Zurich, Zurich, Switzerland, [13]Medical University of Graz, Graz, Austria, [14]Department of Therapeutic Radiology and Oncology, Comprehensive Cancer Center, Medical University of Gra, Graz, Austria, [15]Department of Radiation Oncology, University Medical Center Schleswig-Holstein, Kiel, Germany*

Purpose/Objective(s): To develop expert recommendations for multi-parametric dose prescriptions of SBRT according to ICRU report 91 to harmonize current SBRT practice and clinical trial design.

Materials/Methods: Based on results of a working group literature summary a 2-tier Delphi-consensus process of 24 physician and physics experts from 3 European countries was conducted. Degree of consensus was predefined for overarching (OA) and organ specific (OS) statements (≥80%, 60-79%, <60% for high, intermediate and poor consensus). Post first round, statements were refined in a live discussion with 125 participants for the second round of the Delphi process.

Results: Experts consented on a total of 14 OA and 17 OS statements of SBRT of primary and secondary lung as well as liver, pancreas, adrenal and kidney tumors. Degree of consent was ≥80% in 79% and 41% of OA and OS statements, respectively, with higher consensus for lung compared to upper abdomen. In round 2, degree of consent ≥80% increased to 100% for OA and 88% in OS statements. No consensus was reached for dose escalation of liver metastases after chemotherapy (47%) and single fraction SBRT for kidney primaries (13%). In round 2, no statements had 60-79% consensus.

Conclusion: In 29 of 31 statements a high consensus was achieved after a 2-tier Delphi process, and 1 statement (kidney) was clearly refused. The Delphi process was able to achieve a high degree of consensus for dose prescription of SBRT. In summary, clear recommendations for both OA and OS could be defined. This contributes significantly to harmonization and for the design of clinical trials in SBRT. Specific exemplary cases will be deducted from the statements in the next step.