Materials/Methods: We retrospectively pooled a large cohort of patients with head and neck cancer treated with definitive radiation from 2008 to 2018 at a single institution. 59 patients were available for analysis (15 patients with LR). Each patient underwent a planning CT scan, an FDG PET scan, and an attenuation corrected (AC) diagnostic CT scan prior to radiotherapy. The gross tumor volume (GTV) was manually drawn on the planning CT. The AC CT scan was diffeomorphically warped to the planning CT using Advanced Normalization Tools (ANTs: http://stnava.github.io/ANTs/), and the transform was applied to the FDG PET scan. 6321 radiomic features (2077 from each of the three scans) from within the GTV mask were extracted using Pyradiomics package. The extracted radiomics features included first order spatial statistics, shape-based volumetrics, and gray level matrix operations on the original image as well as derived images using a variety of spatial filters. Dimensionality reduction was performed using a logistic regression model, reducing the feature dimensions from 6321 to 2754. The remaining features were then fed into a variety of machine learning models to train (N = 35) and validate (N = 24) the predictive model with a balanced number of recurrences in the training and validation sets. The model performance was evaluated using receiver operating characteristic (ROC) curve. We further identified the most important features that may affect prognosis.
Results: The machine learning models were able to significantly predict locoregional recurrence in our cohort of 59 patients. The classifier performance of the random forests model revealed an area under the curve (AUC) of 0.81 +/- 0.13. The top feature weights used a combination of features from all three scans, indicating the need for the multi-modal approach of all three scans.
Conclusion: We built machine learning models that can be used to predict locoregional recurrence in patients underwent head and neck radiation using pre-treatment PET and CT scans. This model can be applied to better stratify patients based on pre-treatment images towards personalized treatment. We used automated advanced non-linear registrations and neural networks to improve performance from prior models. The approach can be tailored to optimize medical management using data-driven models.
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Healthcare Staff Sentiment Of Clinical Machine Learning Implementation On The Prospective System For High Intensity Evaluation During Radiotherapy (SHIELD-RT) Study

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Purpose/Objective(s): Despite enthusiasm for clinical artificial intelligence (AI) and machine learning (ML), prospective data remain limited. ML has significant obstacles with respect to clinical integration and provider/patient trust. We recently completed one of the first prospective, randomized studies of clinical ML with a quality improvement (QI) study, which demonstrated that ML-directed evaluations reduced the rate of acute care visits (emergency visits and hospital admissions) during radiotherapy (RT) or chemoradiotherapy (CRT). We report a staff survey to assess reactions regarding the implementation of ML-directed clinical strategies.
Materials/Methods: This was a single institution survey to gauge response to a prospective QI study (NCT03775265) during which all outpatient adult courses of RT and CRT started from January 7, 2019 to June 30, 2019 were evaluated during their first week of treatment by a ML algorithm to identify patients with >10% risk of acute care visits during RT. These high-risk patients were randomized to standard weekly versus mandatory twice-weekly on-treatment visits. All attending and resident physicians, advanced practice providers, nurses, and radiation therapists active during the study were invited to participate in an anonymous survey. The survey included 8 questions on a Likert-like scale, and 2 identifying practice and roles.
Results: A total of 59/71 (83%) staff responded, including 14/16 attending physicians, 9/9 resident physicians, 3/5 advanced practice providers, 10/11 nurses, and 23/30 radiation therapists. Staff did not feel the study disrupted their workflow, with 81% disagreeing or strongly disagreeing. Only 51% agreed or strongly agreed that they were aware of their patients undergoing intervention. Similarly, only 3% agreed that their clinical management beyond the study intervention was altered. Of those aware of patients seen twice weekly, 67% agreed or strongly agreed with the ML-based risk categorization. Most staff (64%) neither agreed nor disagreed that patients understood the study. Future adoption was viewed favorably, as 75% agreed or strongly agreed that they would implement the intervention routinely if the study was positive. Staff indicated that their opinion of clinical ML improved, with 41% expressing agreement or strong agreement and none disagreeing.
Conclusion: Our study demonstrates good reception to the implementation of an ML-based algorithm in the clinical workflow. A pragmatic and streamlined integration with behind-the-scenes alerts minimizes the cognitive burden and disruption to staff. Current efforts focus on operationalization and methods for patient education.

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A Blinded Prospective Evaluation Of Clinical Applicability Of Deep Learning-Based Auto Contouring Of OAR For Head and Neck Radiotherapy

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Purpose/Objective(s): Contouring Organs at Risk (OAR) is time-consuming and highly inhomogeneous among physicians; it affects the accuracy of high precision image-guided radiotherapy. Artificial intelligence (AI) can accelerate OAR delineation and homogenize volume definition. This study aims at blindly evaluating two versions of an AI-based automatic delineation software for OAR.
Materials/Methods: The software tested is a CE-marked software for automatic contouring of more than 80 OAR harnessing a unique combination of anatomically preserving and deep learning annotation concept. This study involved 100 patients with head and neck tumors, retrospectively selected from two French Cancer Centers, for whom clinical expert's annotations that were used for treatment were retrieved. Two subsets of data were randomly created, the first mixing 50% of expert-delineated contours and 50% of software v1.0-generated contours, the second mixing (1/3 each) expert-contours and software v1.0 and v2.0 contours. v1.0 was trained using on average 6,000 cases per organ, while v2.0 used 21,000, in both cases after data augmentation. Contours of 16 OARs were generated and scored by 5 experts and then 4 OARs (mandible, M; brainstem, BS; optic nerve, ON; submandibular gland, SG) were scored again by two experts (PB and VG), as A/acceptable, B/ acceptable after minor corrections, C/not acceptable. Dice similarity coefficient (DSC) and Hausdorff distance (HD) were also computed.
Results: For the first set of data, 96% of all manual contours were classified as clinically useable (75% and 21% in A and B categories,

respectively), compared to 95% for auto-contours (56 % and 39 % in A and B, respectively). Using software v2.0, contours classified as clinically useable (A + B) increased significantly, reaching 100% for M, 98% for BS, 98% for ON and 92% for SG, versus 100%, 97%, 63% and 50% for v1.0, respectively. When the two datasets were compared, intra- and inter-observer rating (score A, B or C) reproducibility was rather poor, ranging from 26% to 78% for the 4 OARs. When only looking at score A+B vs C the reproducibility among observers increased, ranging between 50% and 98%. For ON and SG, mean DSC improved from 0.53 to 0.70 and 0.70 to 0.78 between v1.0 and v2.0 of the software, whereas mean HD decreased by 30% and 17%, respectively.

Conclusion: This study illustrates the potential of AI for automatic contouring of OAR in radiotherapy planning. Automatic contouring with this CE-marked software was very close to expert contouring and clinically usable in the vast majority of cases. Evaluation of automatic algorithms requires objective metrics as illustrated by the disagreement between experts. Evaluation of the impact of contour delineation heterogeneity on dose distribution remains is in progress.

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Time-Driven Activity-Based Cost Analysis of Radiation Treatment Options for Pancreatic Cancer

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Purpose/Objective(s): Several treatment options for resectable and borderline resectable pancreatic cancer exist, including multiple radiation therapy (RT) techniques: conventionally fractionated intensity-modulated RT (IMRT), hypofractionated RT, and stereotactic body radiation therapy (SBRT). However, the differences in provider care delivery costs for each modality are largely unknown. Using time-driven activity-based cost (TD-ABC) models, we quantified institutional costs associated with RT for pancreatic cancer.

Materials/Methods: Comparisons were made between (1) 28-fraction IMRT (IMRT-28) to 50.4 Gy (2) 15-fraction IMRT (HYPO-15) to 67.5 Gy, and (3) 5-fraction SBRT (SBRT-5) to 40 Gy. Process maps were outlined from consultation through follow-up 3 months post-treatment. Process times were determined through panel interviews, and personnel costs were extracted from institutional salary data. The capacity cost rate was determined for each resource, which was multiplied by activity time to calculate costs, and were ultimately summed to determine total cost.

Results: Full-cycle costs of SBRT-5 were 35% lower and 25% lower compared to IMRT-28 and HYPO-15, respectively. Full cycle costs of HYPO-15 were 14% lower than IMRT-28. Technical costs for SBRT-5 were 52% lower and 43% lower compared to HYPO-15 and IMRT-28, respectively. Technical costs of IMRT-28 were 16% lower than HYPO-15. Personnel costs of SBRT-5 were 32% lower and 6% lower than IMRT-28 and HYPO-15, respectively. Personnel costs of HYPO-15 were 28% lower than IMRT-28.

Conclusion: Resource utilization differs considerably among the various RT regimens. By identifying and quantifying the individual processes involved in radiation treatment delivery for pancreatic cancer, this analysis supports the institutional resource efficiency of SBRT-5. Integrating clinical outcomes with resource and cost data will provide further insights into the highest value treatment modalities and thus, may guide alternative payment models, operational workflows, and institutional resource allocation.

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Accountability Of Resources And Cost For Different Modalities

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Purpose/Objective(s): To evaluate feasibility in terms of cost for special treatment procedures across different modalities. An analysis of the cost of alternative state of the art treatment modalities was done to evaluate the necessity of more treatment options, compared to the financial gain provided by each.

Materials/Methods: We used the 2019 Hospital Outpatient Prospective Payment System (HOPPS) to determine reimbursement for each treatment and assumptions on the time of physicist involvement, treatment planning, treatment time, time of radiation oncologist involvement (e.g. for gammaknife where the radiation oncologist stay during treatment), number of fractions per patient, average salaries and initial cost of modality and continuing cost of service contracts. We assumed one source exchange for gammaknife to extend its useful live. We did not include any existing overhead that will be the same between these modalities, rather just the cost of what is needed additionally for some modalities. We determined the maximum number of fractions that can be treated annually for each modality and the expected lifetime of each modality. We then calculated the number of patients needed annually to cover cost.

Results: For stereotactic radiosurgery modalities, i.e. CyberKnife, Linac-based, Linac/MRI, and gammaknife, the annual breakeven points were 25, 34, 41, and 74 patients respectively. For HDR the breakeven was 31 patients each year and 10 for a hyperthermia unit. For protons the number is higher with 152 patients. For each modality there is a limit on the number of patients that can be treated annually, depending on treatment time and common fractionations used for each modality. This favored Linac-based SRS and SBRT where the annual capacity was 1020 patients, because it was assumed that they are dedicated to stereotactic treatments, i.e. few fractions per patient and fastest treatment time. The annual capacity of patients treated with protons were 254, because of the assumption of 25 fractions per patient on average. For Gammaknife, CyberKnife, Linac/MRI, hyperthermia, and HDR the limits were 524, 331, 337, 104, and 433 respectively, because of long treatment times and/or planning times.

Conclusion: Although hyperthermia needed the lowest number of patients to breakeven, its gain and limit on patient's treated annually were the lowest because of a large need of physics and therapy time and relatively high service contracts. For large centers where there might be a larger number of patients that might benefit from a given modality, the cost can be reduced as staff gain more expertise to do these cases faster. Accountability for resources must be balanced by the number of patients that might benefit from it. Having more options of different modalities for state-of-the-art patient care might increase the potential number of patients and a center's research potential, but it will also decrease the gain of each modality because of staff's time, expertise, and service cost.

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