oxidation with glycolysis only under hypoxic conditions. This indicates that adenocarcinomas exhibit glycolysis under normoxic conditions, whereas squamous cell carcinomas are exposed to diffusion-limited hypoxia resulting in a very high anaerobic glycolytic rate. Consequently, FDG-PET should be interpreted in relation to histology. The FDG PET interpretation based on histology improves its prognostic and predictive potential prior to treatment and allows monitoring of treatment efficacy during treatment.

**Objectives are:**

Disease grading, targeting therapies and evaluation of disease biomarkers on early disease diagnosis, disease phenotyping, development of population studies. The identification of early biomarkers and surrogates, and the recently emerged for advancing on the study of rare diseases, with oncology data are needed. These virtual biobanks To further develop this strategy, medical imaging biobanks and finally conducting tests on the principle, efficacy, and the different statistic measures and histogram distribution; displaying the parameterized data appropriately; obtaining reconstructed data with computer and statistical models; molecular images in a multimodality approach; analyzing standardized and optimized anatomic, functional, and biological processes, diseases, or the response to treatment. Imaging biomarkers are defined as objective characteristics extracted from medical images that are related to normal biological processes, diseases, or the response to treatment. Imaging biomarkers evaluate the in vivo properties by in silico modelling of different tissue and lesion properties. These patient specific features are resolved in space (parametric images) and time (longitudinal changes), and can be compared to normal population based data. To develop an imaging biomarker, it is necessary to carry out a series of steps to evaluate reproducibility, technical standardization, validation of the relationship with the studied object and situation, and finally checking its clinical meaningfulness. This process includes defining proofs and tests for the concepts and mechanisms; obtaining standardized and optimized anatomic, functional, and molecular images in a multimodality approach; analyzing reconstructed data with computer and statistical models; displaying the parameterized data appropriately; obtaining the different statistic measures and histogram distribution; and finally conducting tests on the principle, efficacy, and effectiveness of the biomarker.

To further develop this strategy, medical imaging biobanks with oncology data are needed. These virtual biobanks recently emerged for advancing on the study of rare diseases, the identification of early biomarkers and surrogates, and the development of population studies. Oncologic imaging biobanks will evaluate the impact of new biomarkers on early disease diagnosis, disease phenotyping, disease grading, targeting therapies and evaluation of disease response to treatment. In this presentation, I aim to explain the steps that must be established to enable oncologic biomarkers to be correctly applied, from their theoretical conception to their clinical implementation. The learning objectives are:

- To recognize the qualitative and quantitative information of the different modalities.
- To learn about the commonly applied imaging tools in assessing neoplasm size, volume and extension.
- To know the current applied method for quantification of tumor aggressiveness and response to treatment.
- To go through a critical review of criteria actually used in oncologic stratification and management.
- To become familiar with the most appropriate functional imaging biomarkers of tumor activity (perfusion, diffusion, oxygen).
- To appreciate the clinical role of these techniques in planning therapeutic strategies.

**Results:**

For each of the pairwise combinations of functional parameters, obtained Spearman correlation coefficients varied strongly between patients. Resulting median correlation coefficients of the patient cohort are shown in Table 1. Highest correlations were observed for the combinations $v_r/K^{\text{trans}}$ (median: 0.58; range: 0.49 - 0.84), FDG/FMISO (0.57; 0.09 - 0.79), ADC/FDG (-0.38 - 0.15), $v_r/v_p$ (0.36; 0.23 - 0.61), $K^{\text{trans}}$/FDG (0.31; 0.11 - 0.59) and ADC/FMISO (-0.31; -0.72 - 0.2).
Conclusions

Functional PET and MR data showed an incoherent picture of correlations between different parameters, indicating complementary information. While only weak correlations were observed in the median over all datasets, distinct correlations were present on an individual basis. For the combinations FDG/FMISO and AD C/FDG correlations up to -0.79 and -0.85 were observed, respectively. However, limitations may arise from the low number of patients and differences in tumor localization and stage. More patient data is needed to clarify whether subgroups of HN tumors can be identified for which parameter correlations exist. Moreover, in a further step potential correlations between three or more datasets need to be analyzed.

OC-0018
Predicting pathological response in rectal cancer patients: a "PET Radiomic" approach with independent validation

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Purpose/Objective: In personalized medicine, early prediction of response to chemo-radiotherapy (CRT) in locally advanced rectal cancer (LARC) is essential to tailor treatment. Radiomics, a high throughput approach to extract and mine a large number of quantitative features from medical images, may be of added value. This study aimed to investigate and independently validate the predictive value of radiomic features derived from pre-treatment 18F-FDG PET images for pathological tumor stage (ypTN) after preoperative CRT in LARC.

Materials and Methods: As training cohort, 324 LARC patients accrued at our institute between 2005 and 2011 (NIH registered), were included. As validation cohort, 57 LARC patients accrued between 2009 and 2011 at an external institute (NIH registered) were included. Patients received CRT, followed by total mesorectal excision. Patients underwent 18F-FDG PET imaging at baseline (Figure 1a). The tumor volume was semi-automatically delineated with a signal to background based SUV threshold. In total, 166 radiomic features were extracted, comprising: i) first-order statistics (stats) (N=15), ii) intensity volume histogram (IVH) (N=95), iii) shape (N=11), and iv) texture (N=44). Based on review of the resected specimen, patients were grouped into responders (ypT012N0) and non-responders (ypT2+N0+). First, the feature space was reduced by (1) selecting features that are stable in both a test-retest and inter-observer setting (determined in other cohorts) and (2) correlation based hierarchical cluster analysis. Logistic regression was used for predictive modelling and model performance was defined as the area under the receiver operating characteristic curve (AUC). The most predictive features were identified in the training cohort, using a cross-validated forward feature selection scheme. The out-of-sample model performance in the training cohort was determined using 100 rounds of 10-fold stratified cross-validation, followed by independent external validation.