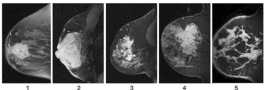


To investigate if MRI morphologic phenotypes defined by unsupervised clustering is associated with breast cancer subtype and pathologic complete response (pCR) after neoadjuvant chemotherapy (NAC)

- **Shape and morphology** are known features associated with tumor malignancy and aggressiveness.
- **Radiomic features** extracted from MRI images provide comprehensive tumor characterization
- While supervised learning uses labeled datasets that train algorithms to classify data or predict outcomes, **unsupervised learning** algorithms are used to examine and group unlabeled datasets. Such algorithms can uncover hidden and intrinsic structures within the data.



1-5 represent different MRI phenotypes

- **990 patients** enrolled in I-SPY 2 TRIAL, randomized to drug arms (NAC)

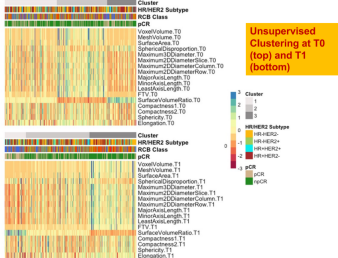
- In ISPY-2, MRI was measured during NAC at pre-treatment (T0), 3 weeks (T1), 12 weeks (T2), and pre-surgery (T3) time points

- **4 subtypes** defined by immunohistochemistry (IHC) based on hormone receptor (HR) and HER2 status:  
HR+/HER2-; HR+/HER2+; HR-/HER2+; HR-/HER2-

- **17 shape features** are defined by **IBSI** (Image Biomarker Standardization Initiative)<sup>1</sup>
- They were extracted by using **PyRadiomics** and measured within the **FTV masks** from **DCE-MRI**.

- MRI morphologic phenotypes: **unsupervised hierarchical** (Pearson correlation, agglomerative ward linkage) on radiomic shape features.
- The associations between the unsupervised clusters of radiomic features with four IHC subtypes and pCR :  **$\chi^2$  test** of independence and **Cramer's V**.

- Optimal number of clusters (**k=3**) was selected from Consensus Clustering<sup>2</sup> method.
- Clusters generated by unsupervised **hierarchical clustering** in a population of **910** out of 990 patients.



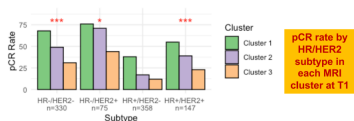
- Features tended to group as those related to **volume** and **surface area**, **linear dimension** and **shape characteristics** such as **elongation** and **flatness**.

- Associations of MRI clusters with pCR are **stronger at T1** than at T0
- Associations of MRI clusters with subtype was **significant** at T1, but not at T0
- Features showing strongest association with pCR included **surface-to-volume ratio** in cluster 3 at T0 and T1, **linear dimension features** in cluster 3 at T0, and cluster 1\_3 at T1

Subtype/Outcome	p-value (χ2 test)	Cramer's V
	T0	
HR/HER2	0.497	0.054
pCR	0.033	0.086
	T1	
HR/HER2	<0.001	0.154
pCR	<0.001	0.233

### Test of association between clusters and IHC subtypes and pCR at T0 and T1

- Highest in Cluster 1 and lowest in Cluster 3.
- **HR+/HER2-**: the pCR rate in Cluster 1 was 2-fold of Clusters 2 and 3-fold of Cluster 3.
- Statistically significantly different except for the HR-/HER2+ sub-cohort



- **Statistically significant association** was shown between MRI morphologic phenotype and pCR, with stronger association observed at T1.
- **Association differed by HR/HER2 subtype** with strongest association observed in HR+/HER2- and triple negative.
- Our results suggest that unsupervised clustering of radiomic shape features derived from DCE-MRI may be helpful for **early prediction of tumor response to NAC**.

MRIs show three-dimensional information such as tumor size and shape. Measuring tumor shape using an unsupervised learning approach as described in this poster can improve the effectiveness of MRI in measuring treatment response. **Early prediction of both responders and non-responders will increase treatment optimization** by allowing responders to switch early to their next scheduled trial therapy while allowing non-responders to switch early to a different trial therapy thereby avoiding side effects from a therapy which is not working for them.

Monti, S., Tamayo, P., Mesirov, J. & Golub, T. Consensus clustering: a resampling-based method for class discovery and visualization of gene expression microarray data. *Mach. Learn.* 52, 91–118 (2003).

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