REAL WORLD DATA AND RESEARCH IN RADIOTHERAPY: WHY, WHAT, HOW?

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Maastro

Contact

SCAN ME

IS RESEARCH ON RT OUTDATED IN THE ERA OF PERSONALIZED MEDICINE?

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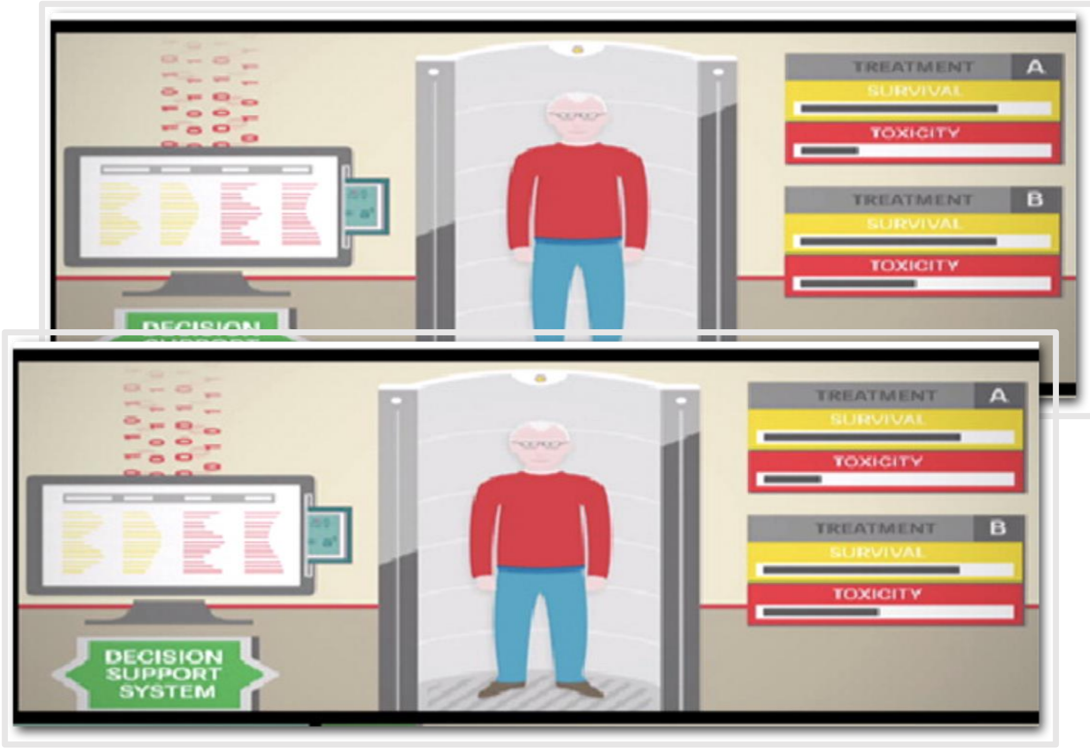
EXPLOSION OF TREATMENTS, DECISIONS, DATA



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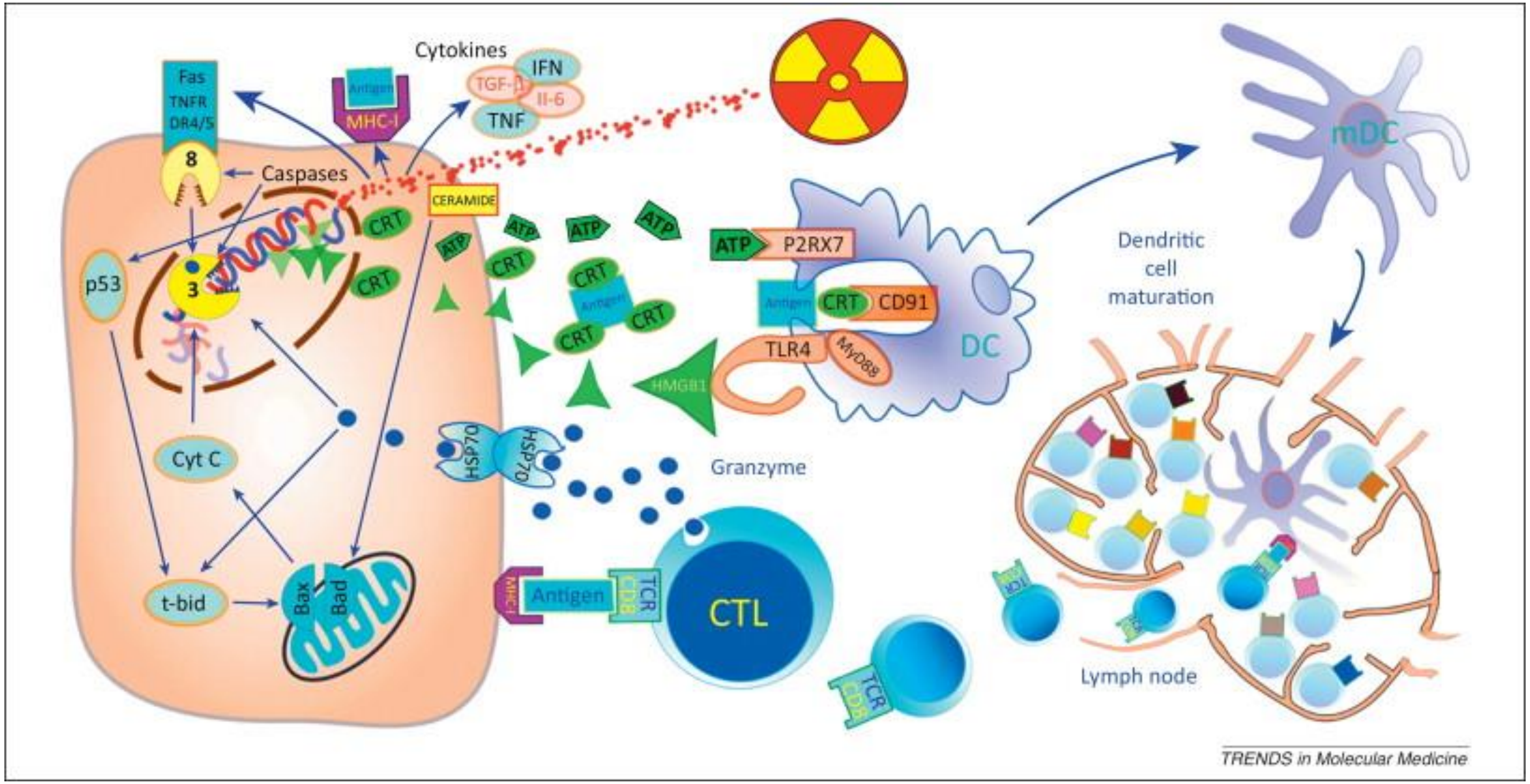
THE MULTICOLLINEARITY PROBLEM



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PERSONALIZED MEDICINE IN RT

Response

Tumor

Side-effects

Host

(Immune) Profiling

Tumor,
Host

P (success) = [P (response) – P (side-effects)] x W (Profiling)

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TECHNOLOGY /DATA LANDSCAPES

(AI) Landscapes

Pharma

Biomarkers

Pharma

Invasive

Pharma

Biology-driven

RT

Surrogates

RT

Imaging-based

RT

AI-driven (radiomics, deep learning)

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TECHNOLOGY REPOSITIONING

(AI) Re-positioning

Fundamentals
Computer vision outside medicine

Re-positioning 1
AI Diagnostic tools

Re-positioning 2
Radiomics, deep learning

Re-positioning 3
Pharma, ”AI companion”

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EXAMPLES IN THORACIC ONCOLOGY

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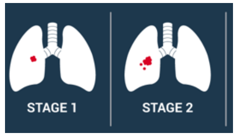
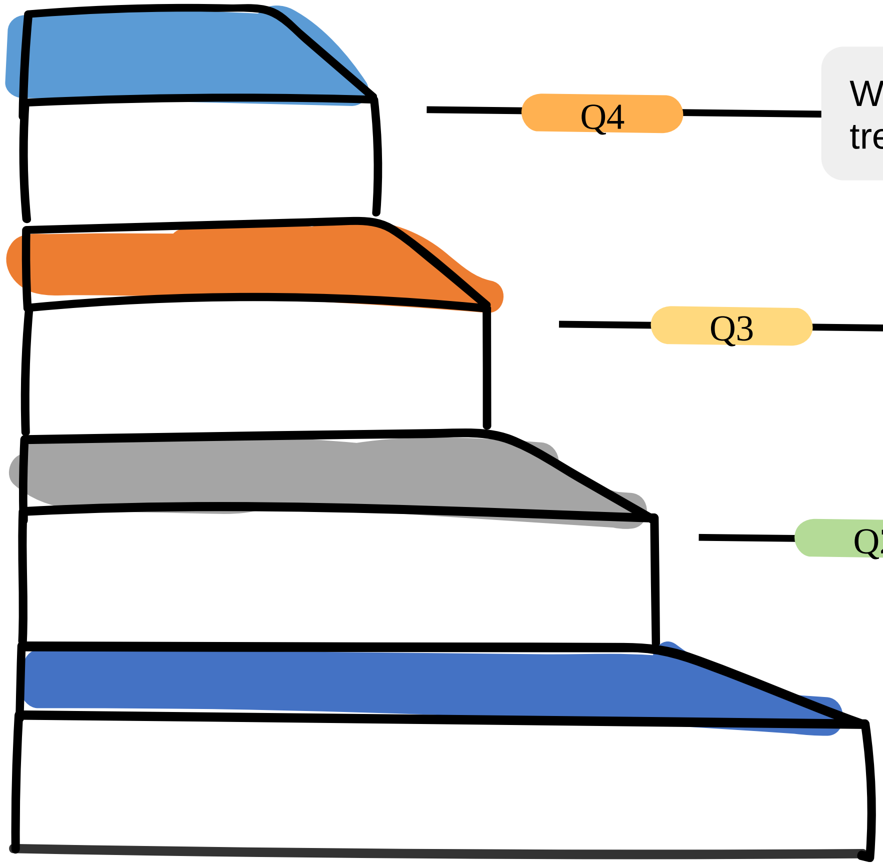
EARLY STAGES





Q4 — Who should receive adjuvant treatment?

Q3 — Who should receive SBRT vs surgery?

Q2 — Can we ”measure” tumor “aggressiveness” ?

Q1 — Can we better detect lung cancer?

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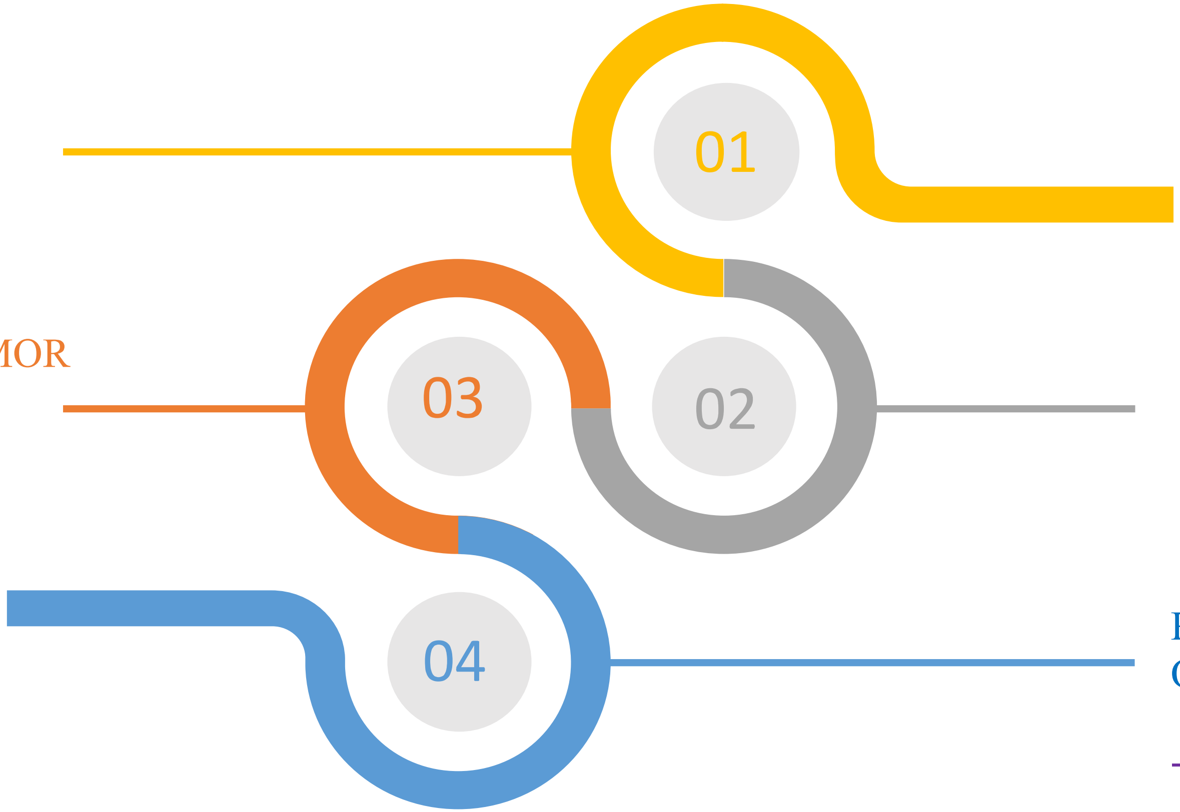
LOCALLY ADVANCED

Review

Artificial Intelligence Applications to Improve the Treatment of Locally Advanced Non-Small Cell Lung Cancers

Andrew Hope [1,2,†], Maikel Verduin [3,†], Thomas J Dilling [4], Ananya Choudhury [3], Rianne Fijten [3], Leonard Wee [3], Hugo JWL Aerts [5,6,7], Issam El Naqa [8], Ross Mitchell [8], Marc Vooijs [3], Andre Dekker [3], Dirk de Ruysscher [3,‡] and Alberto Traverso [3,*,‡]



AUTOMATION OF CLINICAL PROCESSES
- Contouring
- Standardization

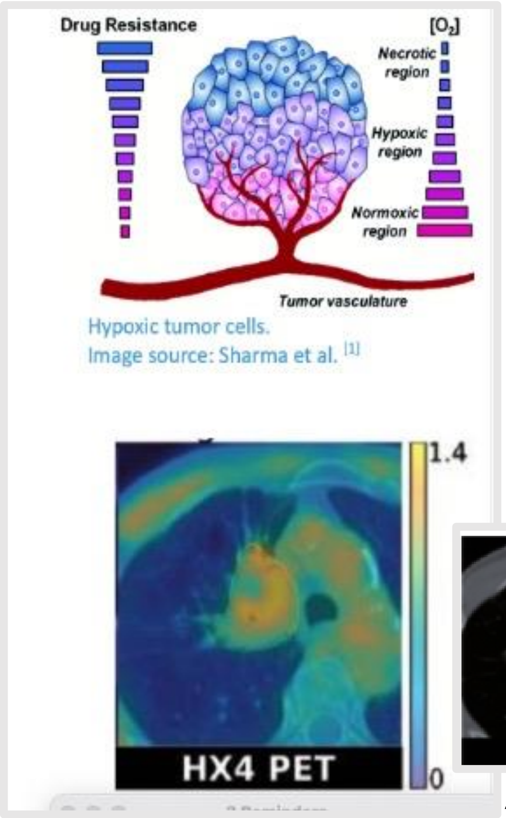
PROGNOSTICATION / PREDICTION
- Toxicities
- Recurrence
- Response

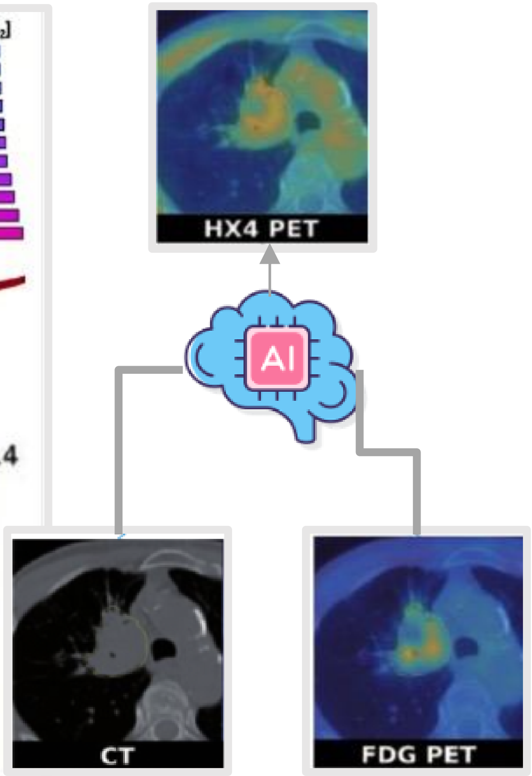
"HOST" AND TUMOR ENVIRONMENT
- Frailty assessment
- Biology

RT WORKFLOW OPTIMIZATION
- Auto planning
- Adaptive RT

“HOST” AND TUMOR ENVIRONMENT

- Frailty assessment
- Biology





Anatomy

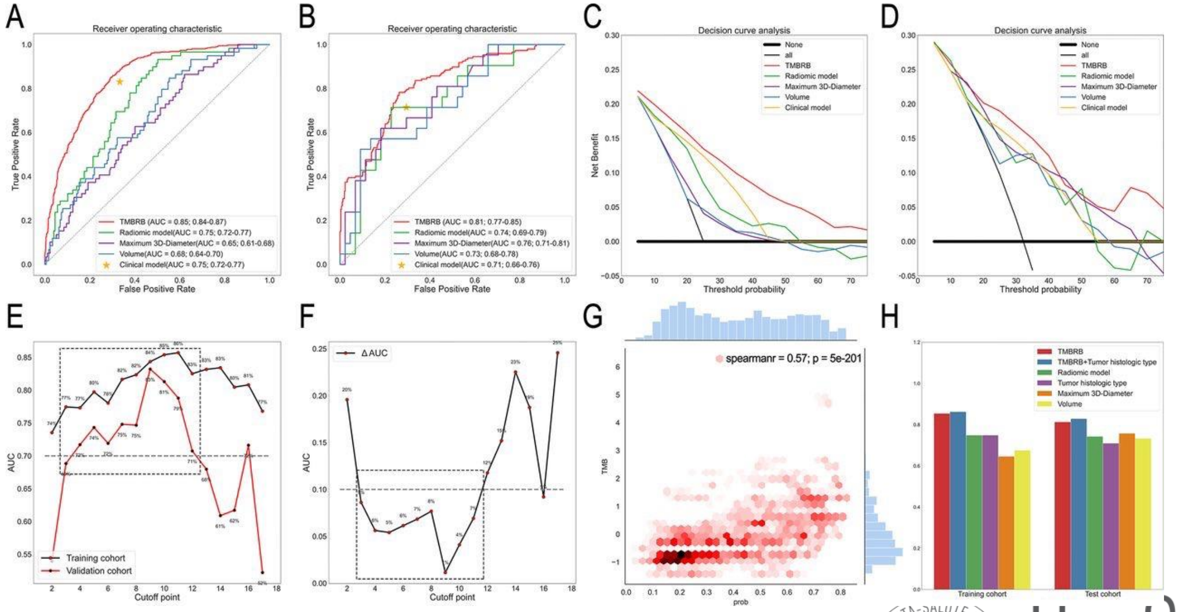
Metabolism

Rao, De Ruysscher

Predicting response to immunotherapy in advanced non-small-cell lung cancer using tumor mutational burden radiomic biomarker

Bingxi He [1,2], Di Dong [2,3], Yunlang She [4], Caicun Zhou [5], Mengjie Fang [2], Yongbei Zhu [2,6], Henghui Zhang [7], Zhipei Huang [1], Tao Jiang [5], Jie Tian [2,6,8,9] and Chang Chen [4]

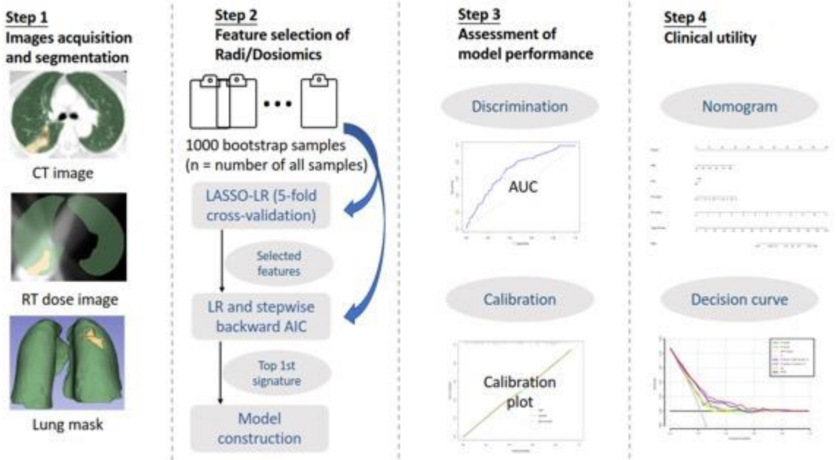
Correspondence to Professor Chang Chen; chenthoracic@163.com; Professor Jie Tian; jie.tian@ia.ac.cn; Dr Tao Jiang; tonyjiangdr@163.com; Professor Zhipei Huang; zphuang@ucas.ac.cn



Zhang, Wee, Traverso

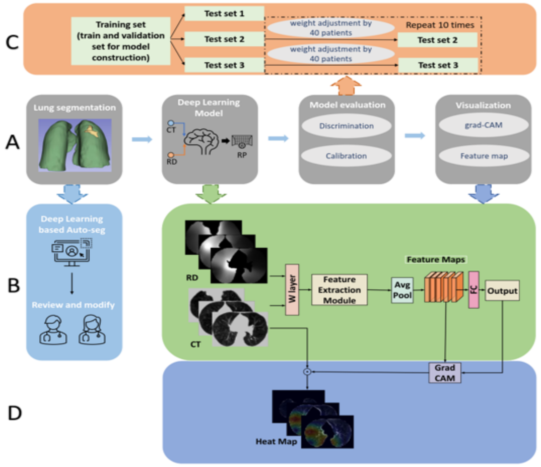
PROGNOSTICATION / PREDICTION

- Toxicities
- Recurrence
- Response



Model	Train (95%CI)	Validation by bootstrapping (95%CI)	Testing (95%CI)
R-score	0.676 (0.606-0.745)	0.619 (0.592-0.646)	0.671 (0.558-0.899)
D-score	0.728 (0.665-0.790)	0.687 (0.667-0.706)	0.684 (0.573-0.883)
DVH-score	0.637 (0.570-0.705)	0.628 (0.613-0.642)	0.661 (0.551-0.856)
Clinical parameters	0.664 (0.594-0.735)	0.654 (0.628-0.680)	0.709 (0.509-0.91)
R-score + DVH-score + C	0.728 (0.674-0.803)	0.719 (0.703-0.736)	0.782 (0.686-0.832)
R-score + D-score + C	0.793 (0.735-0.851)	0.774 (0.762-0.786)	0.855 (0.719-0.990)

Abbreviations: R = radiomics risk score; D = dosiomics risk score; DVH = dose-volume histogram; C = clinical parameters.



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THE ETHERNAL DEBATE ON RCT

Clinical Data
Integration Steps:

Mapping

REQUITE

HYPOG

List Common variables

Unification

For Each Dataset:

1. Select the sources based on the identified common variables
2. Integrate them in single one

REQUITE unified

HYPOG unified

CANTO

Integration

1. Mapping different column names
2. Adjust format for numerical and date format
3. Adjust label for categorical variable

Pre act

Clinical Data:

Outcome occurance

Toxicity	REQUITE	HYPOG	CANTO
Arm Lymphedema	190	307	59
Skin Hyperpigment	956	172	0
Skin Induration	1493	505	1
Telangiectasia	272	121	1
Edema	1062	95	24

Characteristic	REQUITE, N = 2,022[1]	CANTO, N = 3,080[1]	HYPOG, N = 1,259[1]
Baseline.Arm.Lymphedema			
0	1,975 (98%)	0 (NA%)	1,205 (96%)
1	45 (2.2%)	0 (NA%)	49 (3.9%)
Unknown	2	3,080	5
Post.RT.Arm.Lymphedema			
0	1,932 (97%)	0 (0%)	1,104 (91%)
1	58 (2.9%)	3 (100%)	89 (7.5%)
Unknown	32	3,077	66
X12m.follow.up.Arm.Lymphedema			
0	1,751 (97%)	0 (0%)	1,070 (89%)
1	60 (3.3%)	18 (100%)	130 (11%)
Unknown	211	3,062	59
X24m.follow.up.Arm.Lymphedema			
0	1,660 (96%)	0 (NA%)	1,066 (90%)
1	66 (3.8%)	0 (NA%)	120 (10%)
Unknown	296	3,080	73
X36m.follow.up.Arm.Lymphedema			
0	579 (97%)	0 (0%)	1,066 (91%)
1	21 (3.5%)	30 (100%)	120 (9.5%)
Unknown	1,422	3,050	64
X60m.follow.up.Arm.Lymphedema			
0	472 (97%)	0 (0%)	1,165 (95%)
1	16 (3.3%)	22 (100%)	60 (4.9%)
Unknown	1,534	3,058	34
X48m.follow.up.Arm.Lymphedema			
0	274 (96%)	0 (NA%)	1229 (98%)
1	10 (3.5%)	0 (NA%)	23 (1.8%)
Unknown	1,738	3,080	7